Health, Education and Economic Crisis

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Protecting the Poor in Indonesia

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Health, Education and Economic Crisis: Protecting the Poor in Indonesia

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor aan
de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. T. Sminia,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
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door

Robert Albert Sparrow

geboren te Delft

promotor:	prof.dr. J.W. Gunning
copromotor:	dr. M.P. Pradhan

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Amsterdam, January, 2006

Contents

Chapter 1

Introduction

1.1 Health, education and economic crisis: The role of safety nets

When an economic crisis hits, a primary policy concern in developing countries is how the social sectors can be protected and, in particular, how access to social services for the poor can be maintained. Targeted price subsidies, reducing the costs of access for vulnerable groups, are often used as a policy response to macro economic shocks. These could take the form of governments bearing part of the costs of education and health care treatment through reducing fees for public services, reductions in travel time as a result of new facilities being built near poor areas, or price subsidies targeted at specific population groups.

Why should we worry about the delivery of health and education services in times of economic crisis in developing countries?

First of all, accumulation of human resources by investing in health and education is generally considered a key strategy in preventing poverty from being transmitted from one generation to another.[1] Investment by households in health and education are compromised when resource and credit constrained households are faced with unexpected transient income shocks.[2] Under typically incomplete credit markets households have limited scope for transferring wealth across periods, and need to formulate alternative strategies for smoothing consumption. These strategies may include production decisions, such as choosing sub-optimal asset portfolios to reduce income risk, or reallocate household

[1]For a broad discussion see, for example, the World Development Reports of 1990 and 2000/2001 (World Bank, 1990 and 2001, respectively).

[2]E.g. Jacoby and Skoufias (1997).

labour in response to unexpected income shocks.[3] Nevertheless, the literature indicates that households are far from successful in smoothing consumption in response to income shocks.[4] The poor are particularly vulnerable to shocks, given their stringent credit and resource constraints. It is especially hard to insure against covariate shocks, such as a drought or an economic crisis, as both market based and informal insurance and coping mechanisms can break down under macro economic shocks.[5] Households' consumption smoothing strategies may then involve reducing investments in education and health, and drawing on child labour to increase the household income.[6] These decisions affect future income generating capabilities, as reduced investment in education and health decrease human capital accumulation. Households thus face a trade off between current consumption and future productivity, and even a temporary shock can have negative long term welfare effects for the poor if the health and education sectors are not protected.

By lowering the effective price of public social services, government spending enhances access for the poor. However, such a policy of broad targeting may also result in greater leakage of subsidies to the rich.[7] If the rich are more price responsive than the poor, or use the public services more often to start with, they will receive a more than proportional share of the price subsidies. Lowering prices can also have negative consequences for the efficiency of delivery of public services. Especially in health, there is the risk of overconsumption if users, and doctors, are not facing market prices. For these obvious reasons, most developing countries subsidise education and health but do not provide it for free. An important question for policy makers is how changes in prices affect the use of education and health facilities and how these responses vary by income group.

Recently several authors have argued that narrowly targeted social safety nets can play a pivotal role in protecting the poor from macro-economic shocks.[8] Social safety

[3] E.g. Rosenzweig and Wolpin (1993), Murdoch (1995), and Kochar (1999).

[4] See, for example, Morduch (1995 and 1999) and Townsend (1995). Using a Resource Mobilisation survey, Gertler and Gruber (2002) show how Indonesian households are not able to smooth consumption when faced with large income shocks due to illness of the head of household.

[5] E.g. Glewwe and Hall (1998), Morduch (1999), Ravallion (2003), Skoufias (2003). In the case of the Indonesian economic crisis, Frankenberg, Smith and Thomas (2003) find that real per capita consumption declined by about 20 percent in 1998, despite the fact that households adopted multiple strategies to smooth consumption (varying from reorganising household composition to increasing labour supply and selling assets and valuables). See also chapter 2 for a discussion of the Indonesian crisis.

[6] See, for example, Flug, Spilimbergo and Wachtenheim (1998), Dehejia and Gatti (2002), Beegle, Dehejia and Gatti (2003) on the effects of income shocks on schooling and child labour. For empirical work on Indonesia, see Cameron and Worswick (2001) and Fitzsimons (2003). Both papers show that investments in schooling are sensitive to aggregate shocks. In Indonesia, the economic crisis brought about decreased spending on education, especially for primary school children in poor, rural households (Thomas *et al.*, 2004).

[7] E.g. Van de Walle (1998).

[8] E.g. Morduch (1994 and 1999), Ravallion (2003), Ferreira, Prennushi and Ravallion (1999), and Skoufias (2003).

nets can help prevent households adopting coping strategies in a crisis situation that cause long term damage to households' productive capacity and hence economic growth. For example, targeted transfers to specific types of households or employment creation programmes reduce the need for households to sell productive assets or forgo health and education expenses or revert to child labour. Ravallion (2003) argues that the empirical evidence tips the balance in favour of these interventions, despite some bad experiences. He puts a case that in developing countries inequality is not favourable for economic growth due to uninsured risks in the presence of incomplete markets and resource constraints. A main contribution of safety nets is to reduce the threat of dynamic poverty traps by protecting the poorest from transient shocks. *"Market imperfections point to a potential for efficient redistributions, which help alleviate the constraints arising from those market imperfections."*[9]

Additional support for targeted safety nets in health and education comes from the demand literature. Both ex-ante and ex-post studies have emphasised the effectiveness of stimulating the demand for public services amongst the poor through price subsidies. Empirical studies on the demand for health and education typically find high income elasticities, implying large inequalities between poor and rich, but rather low price elasticities that tend to be larger for the poor.[10] Targeted prices subsidies or waivers for costs of medical care and education are therefore often advocated as means to increase access to medical care for the poor. Several studies have further shown that conditional cash transfers and education stipends have positive effects on enrolment and reduce child labour, especially amongst the poor.[11]

However, narrow targeting is not without problems. A large body of literature has been devoted to the difficulties of targeting specific individuals and households.[12] Identifying those eligible for a social programme is constrained by the availability of information, but collecting information is costly. A variety of targeting strategies can be devised, depending on the type of information source and the associated costs. Individual targeting can, for example, be based on centrally collected administrative data such as tax records, or means tests based on a set of individual characteristics. Alternatively, when such information is not available, one can use regional welfare indicators to target regions instead of individuals, or exploit local knowledge by relying on a community based targeting design or the individual private information by introducing a self selection mechanism. How-

[9]Ravallion (2003), p. 14.

[10]E.g. Jimenez (1995), Gertler and Hammer (1997), World Development Report 2004.

[11]E.g. Ravallion and Wodon (2000), Skoufias and Parker (2001), Bourguignon, Ferreira and Leite (2003), Rawlings and Rubio (2003), Maluccio and Flores (2004), Schultz (2004).

[12]See, amongst others, Besley and Kanbur (1993), Van de Walle (1998), Ravallion (2003), and Coady, Grosh and Hoddinott (2004).

ever, when part of the targeting process is decentralised to lower administrative levels, this may introduce incentive problems through asymmetric information between policy makers, programme managers and local officials implementing the programmes. In each case, choosing a targeting design will involve a trade off between the costs of collecting information, the quality of that information, and the degree of control over the targeting process. The empirical literature shows ambiguous results regarding the effectiveness on different targeting mechanisms, with a large degree of heterogeneity both between and within alternative targeting strategies.[13] Success stories are often context specific and there seems to be no clear recipe for successful targeting of social programmes.

1.2 The Indonesian Social Safety Net

In 1997 Indonesia was hit by a severe and unexpected economic crisis, triggered by a financial crisis that affected the whole Southeast Asian region. The economic crisis was characterised by aggregate income shocks and rapid inflation. Up to the crisis, Indonesia had enjoyed a steady improvement in both health and education outcomes. At the onset of the Indonesian crisis, an important concern was whether the achievements made in the social sectors over the past decades could be sustained. To safeguard real incomes and access to social services for the poor, the Indonesian government, with help of donors, introduced the Indonesian Social Safety Net - *Jaring Pengaman Sosial* (JPS) - interventions, which included a health and education programme.

This dissertation addresses a few of the issues raised above, using the JPS interventions in health and education as case study. Chapter 2 sets the stage for the chapters that follow, sketching the context of the Indonesian Social Safety Net. The chapter describes the pre-crisis distribution of health and education services, and the changes in the distributions over the course of the crisis.

The crisis does not seem to have halted the positive trend in enrolment, but it did frustrate improvements in primary and junior secondary enrolment for a year. There is also evidence that expenses on health and education were reduced to smooth consumption during the crisis, in particular for the rural poor.[14] 1999 saw a full recovery, bringing enrolment levels higher than they were before the crisis.

The effects of the crisis are also visible with households' health care utilisation. Increased costs of health care, negative income shocks and deteriorating health services were followed by a strong decrease in health care utilisation, especially at public health care

[13]See Coady, Grosh and Hoddinott (2004) for an extensive review of the empirical literature on the targeting effectiveness of different social intervention programs.

[14]E.g., Frankenberg, Smith, and Thomas (2003), Thomas *et al.* (2004).

facilities. Quality and supply of public care suffered considerably from rising costs of medicine and reduced public health care expenditures, turning people away from public care. In 1999 the public sector enjoyed a revival, but pre-crisis utilisation rates were not achieved.

Chapter 3 contains a detailed description of the JPS interventions, and how the education and health care programmes have been implemented in the first year.

The education programme started in August 1998, at the beginning of the 1998/1999 school year. Almost 4 million scholarships had been made available for primary and secondary schools students. Allocation scholarships followed a partly decentralised process. In a first targeting phase district scholarship quota were set, depending on regional poverty. Poor districts received relatively more scholarships than rich districts. The second phase involved community based targeting, where JPS allocation committees in districts and schools selected children for the programme. The scholarships were monthly cash transfers, which increased in size with enrolment level and amounted to about 7 to 18 percent of average per capita household consumption.

The health care was introduced in the last quarter of 1998. This programme consisted of a targeted price subsidy in combination with a public spending component. The price subsidy operated through a health card - *Kartu Sehat* - scheme. Health cards were targeted to households that were thought to be most vulnerable to effects of the crisis. The health card entitled all household members to the price subsidy at public health care providers. Similar to the education programme, targeting and allocation of health cards was decentralised to districts and village communities. The public spending component of the programme was meant to compensate the public health care facilities for the increased demand due to the health cards. The facilities that provided the subsidised care received extra budgetary support in the form of monthly block grants. However, there was a loose relationship between the utilisation of the health card and the compensation that the health care providers received in return. The block grants were based on the estimated number of households eligible for the health card programme and not on actual utilisation of the health cards.

Both programmes were of considerable size. By February 1999 the programmes were still expanding, yet 11 percent of Indonesians (approximately 22 million people) lived in a household with a health card, while 5 percent of children aged 10 to 18 (approximately 2.1 million children) had received a scholarship.

1.3 Local and geographic targeting

Chapter 3 further addresses the targeting performance of the two JPS programmes, in light of the decentralised design. Particular focus is on the effectiveness of regional targeting policy in contrast to within-district targeting by the local allocation committees. While both programmes have clearly been targeted pro-poor, there is also a large degree of leakage to the non-poor. Targeting problems occurred at both national and local level. The results confirm concerns of other authors that targeting of the JPS programmes was hampered by a lack of reliable data. At the time of implementation only pre-crisis information on regional poverty was available for geographic targeting. But not only did the crisis have a strong heterogenous impact across regions, there was also very little correlation between this impact and pre-crisis poverty.

At local level, the health card programme has not eliminated all barriers to access to health care for the poor. Conditional on receiving a health card, the non-poor are less likely to use it for medical care. Opportunity costs of time and travel costs are relatively high for poor rural households, and the availability of and distance to public facilities determine the effectiveness of the health care subsidy.

Chapter 4 delves into the measurement of marginal benefit incidence. The recent literature on benefit incidence has proposed a number of methods to measure the marginal benefits of social programmes.[15] These methods supplement traditional average benefit incidence in that they investigate to what extent an expansion of an existing programme will be to the benefit of the poor. However, these methods do not tell us whether marginal changes in benefit incidence are due to changes in geographic or local targeting. Chapter 4 proposes a simple micro-simulation based approach to disentangle the effects of local and geographic targeting on distributional outcome of social programmes. This method builds on recent extensions to Oaxaca-Blinder decomposition methods.[16]

The method is applied to the JPS health and education programmes, both of which have expanded from 1999 to 2002. After 1999, when more accurate information on regional poverty became available, the geographic targeting rules were altered. The programmes are targeted pro-poor but the marginal distribution of benefits shows quite different patterns. The poor have been the main beneficiaries of an increase in scholarships, whereas the expansion of the health card does not show a pro-poor pattern. The simulation based decomposition approach investigates to what extent the distributional outcome of the programme's expansion is a result of changes in geographical targeting, changes in local targeting, or simply due to the expansion of the programmes.

[15] For an overview see Younger (2003) and van de Walle (2004).

[16] See Bourguignon, Ferreira and Lustig (2005).

The simulation method can provide more nuance to the observed patterns in targeting of social programmes, and facilitate understanding and interpretation of conventional marginal benefit incidence results. The exercise with the scholarship programme has shown that existing measures for dynamic marginal benefit incidence can sometimes be misleading for social policy advice. The pro-poor marginal incidence observed with the scholarship programme seems to be driven by improved local and geographical targeting over time. Expanding the programme without considering the targeting process would in fact increase leakage to the non-poor. For the health card programme, the decomposition results do not conflict with marginal incidence results. Instead, the results highlights which targeting instruments would be most effective in reallocating health cards to the poor.

1.4 Impact evaluation

Measuring the effect of the scholarships programme on enrolment, school attendance and child labour is dealt with in chapter 5 (which is based on Sparrow, 2004). The main challenge with ex-post evaluations is to obtain a reliable estimate of the counterfactual: what would have happened if the JPS programme had not been implemented? Because of non-random programme placement and data limitations, it requires non-experimental methods to answer this question. The effects of the scholarships are identified by virtue of random geographic mis-targeting at the initial stage of allocation, due to incomplete information on the regional poverty profile and the impact of the crisis. Instrumental variables are constructed from this mis-targeting, using data on the selection rules and ex-post information on the regional poverty.

The scholarship programme has been effective in protecting the access to education, despite the problems with geographic targeting. The programme has increased enrolment, especially for those who were most vulnerable to the effects of the crisis: primary school aged children from poor rural households. The scholarships were also found to increase school attendance of enrolled children, and reduce working activities. Although it was not an explicit goal of the programme, the scholarships raised the reservation wage for students. The cash transfers relieved the pressure on households to draw on the labour of their children to smooth income, especially for the rural poor. However, finding statistically significant and positive effects does not mean that the programme is a complete success. A large part of the funds has been allocated to students who would not have dropped out of school in absence of the programme. For example, the large number of scholarships targeted at secondary schools had little to no impact on enrolment. This implies that more accurate targeting, and redefining target groups, would greatly improve the programme's effectiveness.

Chapter 6 (based on Pradhan, Saadah and Sparrow, 2004) investigates the impact of the health cards on outpatient utilisation. The particular design of the programme provides an interesting policy experiment, and allows a comparison of the effects of a targeted price subsidy with those of increased public health care spending. Because of the weak link between the health card programme and the lump sum grants to facilities, these two components of the programme in effect operated as two separate interventions. The transfers made to public sector providers benefitted all potential users while the price subsidy was available only to those who received a health card. In chapter 6 an attempt is made to disentangle the effects of both programmes.

The results provide a mixed message. First, the price subsidy was clearly effective in increasing health care demand amongst the poor, as the health card increased utilisation and led to a substitution effect from private to subsidised public care. For the non-poor the health card affected only their choice of health care provider without increasing overall utilisation. Second, the revival of public heath care utilisation in 1999 can be attributed to the JPS health programme, but most of this effect is due to improved quality and extra supply of medical care through the budgetary support to public providers. The price subsidy appears to account for only 20 percent of the programme 's overall impact. Third, in absence of clear incentive mechanisms for health care providers, general increases in public spending are ineffective in reaching the poor. The supply induced effect appears to be concentrated with the non-poor. The poor are responsive to a price subsidy but not to a supply impulse, while utilisation of the non-poor is mainly supply driven. In the end, most of the benefits of the programme have gone to the non-poor, despite pro-poor targeting of health cards and their clearly positive effect for the poor.

Chapter 2

The Indonesian Economic Crisis: Trends in Health and Education

2.1 Introduction

In the fall of 1997 Indonesia was hit by a severe economic crisis, exacerbated by social and political turmoil in 1998. Up to the crisis, Indonesia had enjoyed a steady improvement in both health and education outcomes, which went together with economic growth.

Educational attainment increased strongly in Indonesia during the 1970s and 1980s. The trend in gross enrolment from 1971 to 1997 is shown in figure 2.1. In a period of 15 years gross primary school enrolment increased by almost 50 percentage points, exceeding 100 percent by 1985. Secondary school attainment also increased, but is still far from universal. From 1971 to 1996 gross junior secondary enrolment almost quadrupled as it increased from 18 to 67 percent, while senior secondary enrolment increased from 9 to 37 percent. A notable feature of these improvements are the distributional aspects.[1] First, primary enrolment in rural areas has almost caught up with urban enrolment. The urban-rural gap for primary school age children (7 to 12) has decreased from 9 percentage point in 1978 to about 3 percentage point in 1997. For junior secondary age (13 to 15) the gap has decreased from 26 to 16 percentage point. This is partly due to the increased supply of primary and junior secondary education, resulting from large infrastructural investments initiated in the 1970s. This is also reflected by the improvements in education attainment amongst the poor, who have been the main beneficiaries of increased primary education. The difference in primary school age enrolment between the poorest 40 percent and the

[1] For an analysis of enrolment and benefit incidence of public education spending in 1978 and 1987 see Meesook (1984), Chernikovski and Meesook (1985), and van de Walle (1992). Lanjouw, Pradhan, Saadah, Sayed and Sparrow (2002) discuss the trend in enrolment over the last three decades.

richest 30 percent of the population has decreased from 11 in 1979 to 5 percentage point in 1997. Nevertheless, despite the pro-poor trend in secondary education large disparities remain between poor and non-poor. In 1997, school enrolment of rich children aged 16 to 18 is still about twice as high than that of the poor (34 and 64 percent, respectively).

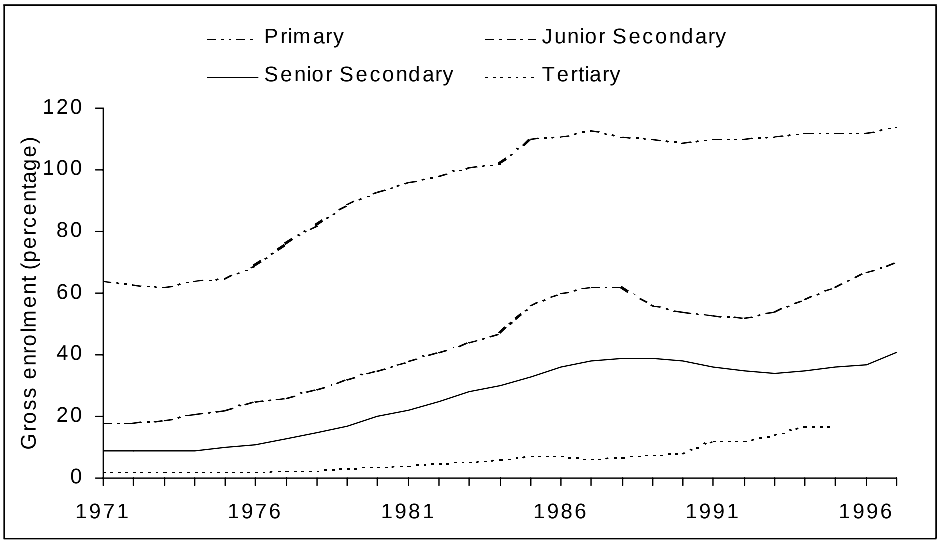

Figure 2.1: Gross enrolment 1971 to 1997, by enrolment level. Source: Lanjouw, Pradhan, Saadah, Sayed and Sparrow (2002).

Similar improvements can be seen for health outcomes. Figure 2.2 shows that from 1962 to 1995 infant mortality dropped from 133 to 51 per 1000 births. The mortality rate amongst children under 5 decreased from 216 per 1000 births in 1960 to 75 per 1000 births in 1995. In that same period life expectancy at birth increased from 42.5 to 64.1. With the expansion of the public health sector the public health centres (*Puskesmas*) have become the most widely used facility, especially amongst the poor and in rural areas.[2] Amongst the poorest 40 percent of the population, almost half of the (self reported) ill did not seek formal care, while approximately a quarter visited a public health clinic. The use of private health care and hospitals is still very much distributed pro-rich.

At the onset of the Indonesian financial crisis, an important concern was whether the achievements made in the social sectors over the past decades could be sustained. The Indonesian government, with help of donors, reacted swiftly by introducing a number of interventions aimed at safeguarding real incomes and access to social services for the poor. The main interventions of this Social Safety Net - *Jaring Pengaman Sosial* (JPS) - were in health and education. Together these constituted 62 percent of the allocated budget

[2]E.g. Chernikovski and Meesook (1986), van de Walle (1992 and 1995), and Lanjouw *et al.* (2002).

for the Social Safety Net programmes in 1998/1999.[3]

This chapter describes the pre-crisis distribution of education and primary health care services, and the changes in the distributions over the course of the crisis. The design and the implementation of the JPS programmes will be discussed in chapter 3. This chapter is setup as follows. The next section gives a short account of the economic crisis and the effect on poverty and public expenditures. As we will see, the crisis was marked by an explosive increase in poverty and real food prices, while the social sectors suffered budget cuts. The last two sections describe the changes in enrolment and outpatient care utilisation, as observed in the Indonesian National Socioeconomic Survey (*Susenas*) from 1995 to 1999, and how this relates to findings from other studies.[4] Despite reports of large reductions in human resource investments by households, enrolment seems to have been affected mildly. The positive trend in enrolment was halted during the crisis, but enrolment rates did manage to exceed per-crisis levels by 1999. Utilisation of outpatient care decreased during the crisis, both in terms of the number of people that visited health care providers and the frequency of visits by these people. Utilisation of public care shows the strongest decrease, which is explained by a decline in quality and supply of public care.

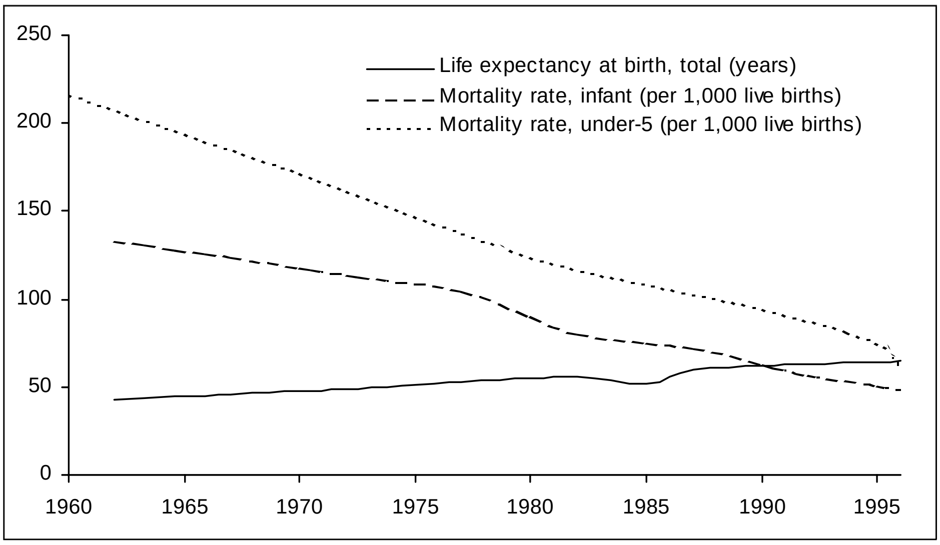

Figure 2.2: Trend in health outcomes 1960 to 1996. Source: *World Development Indicators*, World Bank, 1998.

[3]The JPS further included a food security program, labour creation and micro credit programme. Ananta and Siregar (1999) and Daly and Fane (2002) provide a good overview of all the JPS programs.

[4]These two sections draw on results reported earlier in Pradhan and Sparrow (2000a and 2000b).

2.2 The economic crisis

The Indonesian economic crisis was triggered by a financial crisis that hit Southeast Asia mid 1997. In addition, eastern Indonesia, Java and Sumatra were struck by El Niño related droughts in the second half of 1997, while Sumatra, Kalimantan and eastern Indonesia suffered large forest fires.

By 1998 the effects of the economic crisis were felt all over Indonesia. Real GDP decreased by roughly 14 percent in 1998 and poverty rates had increased dramatically.[5] The economic crisis was accompanied by social unrest and political instability, with violence marring several parts of the country. This culminated in the resignation of president Suharto in May 1998 following deadly clashes between armed forces and student activists demonstrating for reform, and riots in Jakarta that left more than a thousand people dead.

The economic crisis showed considerable heterogeneity across regions, with Java (the most populous island of the archipelago) experiencing the greatest difficulties (Sumarto, Wetterberg and Pritchett, 1998). Also, urban areas seem to have been hit harder than rural areas. Using data from the Indonesian Family Life Survey, Smith *et al.* (2002) show that from 1997 to 1998 mean real incomes decreased by 43 percent for urban and by 21 percent for rural families. Real income decreased for all income groups, but the poor suffered the largest shock. For the poorest 25 percent of the population, real income decreased by 64 and 33 percent in urban and rural areas, respectively.

Real incomes decreased as prices soared. Figure 2.3 graphs the change in the consumer price index from 1997 to 1999. 1998 saw an annual increase in the consumer price index of 78 percent, with the price of food doubling. Especially alarming for the poor was the development of the price for rice and other staple food, which increased by more than 200 percent from July 1997 to September 1998. The price for education and health services also increased, but not as strongly as the food price. Over the course of 1998 prices for health services increased by about 40 percent, for education 10 percent. Note that for some of the poor, such as net food producers, this implies that health and education had become cheaper.

There is little evidence of rising overall unemployment during the crisis. Instead, real wages dropped by about 40 percent in the formal wage sector during the first year of the crisis, and agriculture seems to have absorbed part of the displaced labour from other sectors. The decline in real wages is about twice as high compared to real incomes of households active in the formal sector, indicting alternative income smoothing strate-

[5] See, for example, Cameron (1999) for an account of the events and economics developments during the crisis.

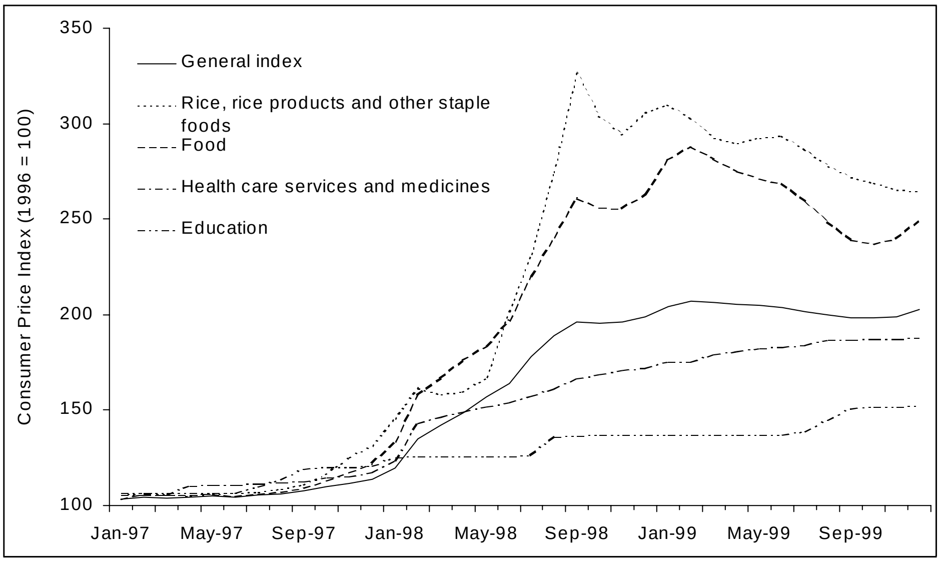

Figure 2.3: Consumer Price Index, January 1997 to December 1999. Source: Central Bureau of Statistics, Indonesia.

gies. The crisis saw large scale migration to rural areas (especially children and elderly), increased household labour activities, and households reverting to agriculture. Other reported coping strategies included spending down on wealth and changing spending on semidurables.[6]

According to official estimates the poverty headcount increased from 17.7 in 1996 to 23.5 in 1999. Alternative estimates of poverty during the crisis abound, unambiguously showing a daunting increase in poverty. Suryahadi, Sumarto and Pritchett (2003) trace the path of poverty from 1996 to 1999 and find that, after a period of steady decline, the poverty headcount has more than doubled during the crisis (figure 2.4).[7] They estimate that from February 1997 to the height of the crisis, late 1998, the poverty headcount increased from 15.3 to 33.2 percent. Of course, the poverty head count is sensitive to the choice of poverty line as it lies close to the mode of the distribution of per capita expenditure (e.g. Dhanani and Islam, 2002; Suryahadi, Sumarto and Pritchett, 2003). But the crisis impact is also reflected in other dimensions of poverty. Skoufias, Suryahadi and Sumarto (2000) find that both the poverty gap and poverty inequality increased stronger than the headcount. This increase in inequality is partly explained by the differential impact of the crisis at the lower end of the income distribution. Real wages declined

[6]See, amongst others, Cameron (1999), Dhanani and Islam (2002), Smith *et al.* (2002), Frankenberg, Smith and Thomas (2003).

[7]Suryahadi, Sumarto and Pritchett (2003) use a variety of data sources on poverty to estimate a consistent set of poverty estimates over time. The main difference with other studies is that they account for the strong relative price changes that occurred during the crisis.

strongest for unskilled labour, while net food producers benefited from the relative price increase in food.[8] This again emphasises the heterogeneity of the crisis, not just across regions, but also across households.

Knowles and Marzolf (2003) report sharp cutbacks in public health spending due to reduced government revenues during the crisis. Real public spending on primary care decreased by 5 percent (107 billion Indonesian Rupiah) in the 1997/1998 fiscal year, and a further 11 percent (205 billion Rupiah) in 1998/1999. The lack of operational funds and shortage of drugs disrupted services in public health care facilities in 1998. Health spending by the Government of Indonesia declined even faster during this period, but this was partly offset by increased donor funding. In 1998/1999 total donor assistance for primary health care spending increased by 163 percent (186 billion Rupiah.). Public spending on education did manage to increase (in real terms) during the first crisis year but then plummeted in the following year. In the 1997/1998 fiscal year total real public spending increased by 1 percent (146 billion Rupiah), after which it fell by 28 percent (3,912 billion Rupiah) in 1998/1999 (World Bank, forthcoming).

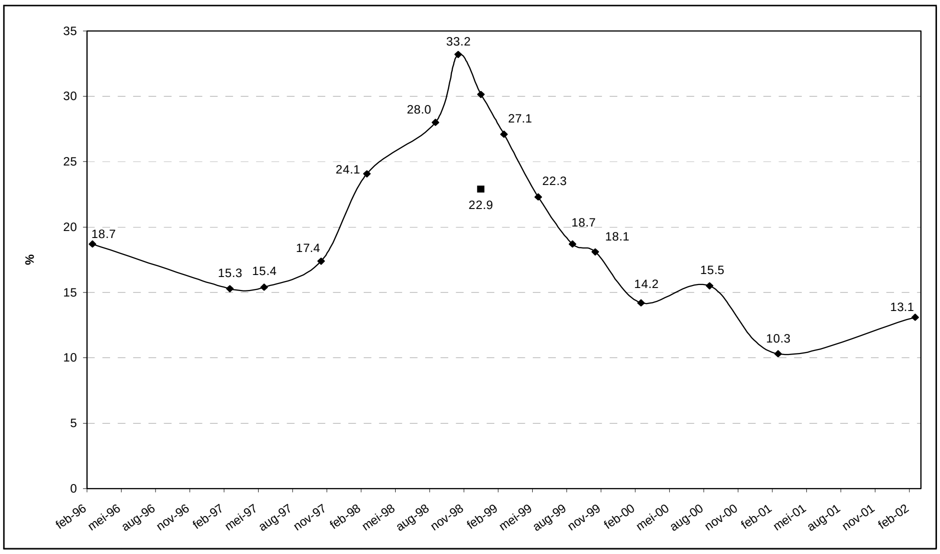

Figure 2.4: The evolution of the poverty headcount from 1996 to 2002. Source: Suryahadi, Sumarto and Pritchett (2003).

[8] Smith *et al.* (2002) note, however, that the positive effects for net food producers may be diminished by the severe droughts and forest fires prior to financial crisis.

2.3 Education

2.3.1 Institutional setting

Basic education in Indonesia consists of 6 years of primary school, followed by 3 years of junior secondary school. Indonesian children are supposed to enrol in primary school at age 7. After graduating from junior secondary school, children can progress to senior secondary school, which takes another 3 years to complete. Officially, basic education is compulsory for children aged 7 to 15, although this is not strictly enforced.

Primary and secondary education is offered by both public and private schools. In principle, each village and urban precinct (*desa* and *kelurahan*) in Indonesia should have at least one public primary school. Junior and senior secondary schools generally serve larger areas, such as sub-districts (*kecamatan*) and districts (*kabupaten* and *kota*). Hence average travel distance increases with enrolment level. In addition to public schools there is a large private sector. The 1998 Susenas reports about 23 percent of all primary and secondary school students to be enrolled in a private school. The share of the private sector increases with enrolment level, with 12, 33 and 47 percent at primary, junior and senior secondary level, respectively. The private sector shows a great degree of heterogeneity, with only a small segment of expensive and high quality schools. The large majority of private schools are considered to be of lower quality and less expensive than public schools. Private schools generally have fewer resources and school inputs, and more part-time and less qualified teachers.[9]

In the 1997/1998 budget year, public expenditure on education amounted to approximately 2.1 percent of GDP. 52 percent of this was allocated to primary education, while junior and senior secondary education received 18 and 13 percent, respectively (World Bank, 1998). Private spending on education is almost as high as public spending (based on the education module of the 1998 Susenas, which collects detailed household expenditure on education).

2.3.2 Education and the crisis

There is some evidence that private spending on education was reduced to smooth consumption during the crisis. Frankenberg *et al.* (2003) find that real household consumption declined by 23 percent in 1998, with investment in human capital (i.e., health and education) decreasing by 37 percent. Thomas *et al.* (2004) find that household spending on education declined, in particular for the rural poor. On average (real) education

[9]Detailed information on Indonesia's education system is given in World Bank (1998).

expenditure per enrolled household member decreased by 19 percent from 1997 to 1999, amongst rural households. They estimate that as a result of the crisis non-enrolment rates for primary school aged children increased by almost 20 percent. Interestingly, households seem to have protected education of the older children at the expense of their younger siblings. An explanation is that expected returns to higher education are larger than for basic education in Indonesia[10], and that households have already invested in secondary education of older children.

A first glance at the Susenas data suggests that enrolment has suffered from the crisis, but only for a short period. Table 2.1 shows that primary and junior secondary school enrolment rates increased from 1995 to 1997, stagnated in the crisis year 1998, but increased again in 1999. Despite the severity of the crisis, a large scale drop out was not observed in 1998. Jones and Hagul (2001) and Jones *et al.* (2003) discuss field evidence of strong community support and commitment of schools to maintain enrolment levels during the first year of the crisis. The following year, when the JPS programme had been initiated, enrolment picked up, exceeding pre-crisis levels. Senior secondary enrolment increased throughout this period, even in 1998. A similar pattern is seen for total enrolment per age group of school aged children.

Table 2.1: Enrolment rates, by education level and age group in 1995, 1997, 1998 and 1999

		1995	1997	1998	1999
Net enrolment	Primary	91.5	92.3	92.1	92.6
		[0.13]	[0.12]	[0.12]	[0.13]
	Junior secondary	51.0	57.8	57.1	59.2
		[0.36]	[0.35]	[0.34]	[0.39]
	Senior secondary	32.6	36.6	37.5	38.5
		[0.38]	[0.39]	[0.37]	[0.42]
Age group	7 to 12	93.9	95.4	95.1	95.2
		[0.12]	[0.10]	[0.11]	[0.12]
	13 to 15	73.2	77.5	77.3	79.0
		[0.32]	[0.30]	[0.30]	[0.32]
	16 to 18	43.9	47.9	48.7	50.4
		[0.41]	[0.40]	[0.38]	[0.41]
	7 to 18	77.5	79.4	79.2	79.8
		[0.18]	[0.17]	[0.17]	[0.18]
Number of observations		250,053	247,908	243,349	235,334

Standard errors in square brackets are adjusted for clustering in survey design.
Source: Susenas 1995, 1997, 1998 and 1999.

[10]See, for example, Behrman and Deolalikar (1995).

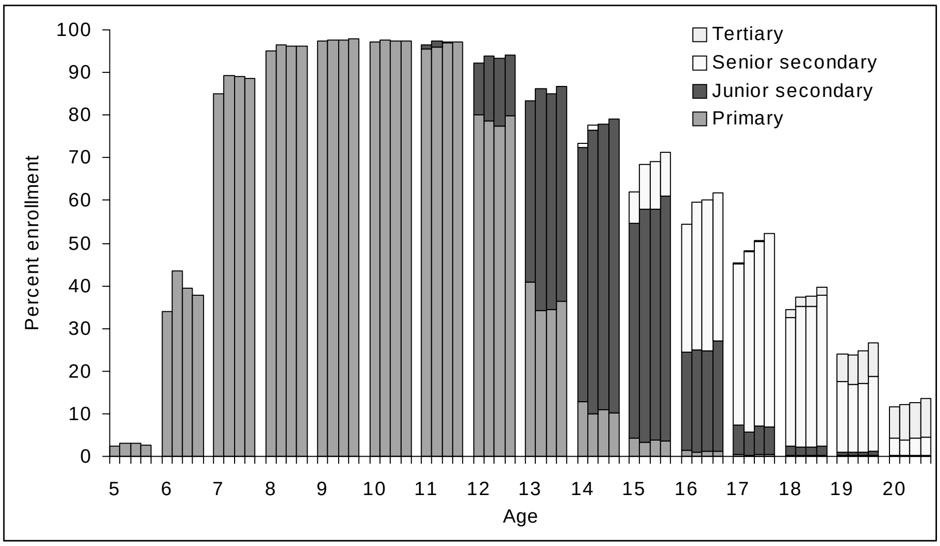

Figure 2.5: Enrolment by age and level, from 1995 to 1999 (percentages, left column is 1995, right 1999). Source: Susenas 1995, 1997, 1998 and 1999.

While the 1999 enrolment rates are higher than ever before, there is some indication of delayed transition from one level of school to the next. Figure 2.5 shows enrolment by age and school level. Delayed enrolment, often due to grade repetition, is not uncommon in Indonesia (Behrman and Deolalikar, 1991; Pradhan, 1998). Delayed enrolment in primary school increased during the crisis, especially for 6 year olds, for which enrolment declined by 5.7 percent point from 1997 to 1999. Also at ages 11 to 13, when children should move from primary to junior secondary, we see an overall increase in enrolment with an increasing share of junior secondary school students. During the crisis this trend reverses as the share of primary schooling increases. A similar trend can be observed for the transition from junior to senior secondary school. At ages 15 and 16, a larger proportion of children was still in junior secondary school then ever before. For 17 and 18 year olds, on the other hand, there is a steady increase in senior secondary from 1995 to 1999. Delays in basic education enrolment are also found in a study by Filmer *et al.* (1999), based on a school survey.

The changes in enrolment by (per capita) consumption quintile are shown in tables 2.2, 2.3 and 2.4. The top panel in the tables show net enrolment, while the bottom gives overall enrolment for specific age groups. The pattern of an overall increase in primary enrolment, from 1995 to 1999, with a small drop in 1998, is also observed for the first, second and fourth quintile (table 2.2). The poor suffered the largest decrease and are the only group that did not recover to the 1997 level. By contrast, the richest quintile enjoyed continued improvements in primary enrolment. The increase in net primary enrolment from 1998 to 1999 is partly due to delayed transition to junior secondary school, as increases in enrolment amongst 7 to 12 year olds is less profound (bottom panel in table 2.2).

At the junior secondary level there are strong improvements in enrolment from 1995 to 1997 for all but the richest quintile (table 2.3). In absolute terms, the poor benefited most from the expansion in the junior secondary school system. Net enrolment for the poorest quintile increased by 12.5 percent points from 1995 to 1999. However, enrolment is still highly correlated with wealth. Except for the rich, all quintiles suffered a dip in junior secondary enrolment during the crisis. Enrolment picked up in 1999 and exceeded pre-crisis enrolment for all income groups. However, for the first to fourth quintiles the increase over the 1997-1999 period is minor compared to the improvements observed from 1995 to 1997. For example, net junior secondary enrolment increased by 28 percent (8.7 percent point) amongst the poor in the two years prior to the crisis, while in the two years following it increased by 6 percent (2.4 percent point).

Table 2.2: Enrolment rates primary school age (7 to 12), from 1995 to 1999, by per capita consumption quintile, gender and area

Net primary enrolment		1995	1997	1998	1999
Consumption quintile	1 (poor)	88.8	90.4	89.6	90.2
	2	92.1	92.7	92.6	93.1
	3	92.5	93.2	93.3	93.8
	4	92.9	93.9	93.1	94.2
	5 (rich)	92.0	92.1	92.6	93.4
Gender	Male	91.4	92.5	92.0	92.6
	Female	91.5	92.2	92.1	92.6
Area	Urban	92.6	93.0	92.8	93.3
	Rural	90.9	92.0	91.7	92.2
Overall enrolment at age 7 to 12		**1995**	**1997**	**1998**	**1999**
Consumption quintile	1 (poor)	89.8	91.8	90.9	91.3
	2	93.7	95.0	94.7	95.0
	3	94.5	96.3	96.2	96.4
	4	96.2	97.5	97.3	97.5
	5 (rich)	98.1	98.6	98.8	98.8
Gender	Male	93.6	95.1	94.9	94.9
	Female	94.3	95.6	95.3	95.6
Area	Urban	96.7	97.8	97.6	97.5
	Rural	92.7	94.2	93.8	94.0

Source: Susenas 1995, 1997, 1998 and 1999.

Table 2.3: Enrolment rates junior secondary school age (13 to 15), from 1995 to 1999, by per capita consumption quintile, gender and area

Net junior secondary enrolment		1995	1997	1998	1999
Consumption quintile	1 (poor)	30.8	39.5	38.7	41.9
	2	42.5	52.3	51.5	53.6
	3	52.9	60.5	60.2	61.8
	4	62.2	68.8	66.8	68.9
	5 (rich)	72.7	74.2	74.5	76.3
Gender	Male	50.7	57.4	56.2	58.5
	Female	51.2	58.3	58.0	59.9
Area	Urban	66.5	70.6	69.7	71.4
	Rural	42.7	50.6	49.6	51.8
Overall enrolment at age 13 to 15		**1995**	**1997**	**1998**	**1999**
Consumption quintile	1 (poor)	56.8	62.1	62.4	65.2
	2	66.5	73.0	72.2	74.8
	3	75.1	79.9	78.7	81.6
	4	82.7	86.5	85.8	87.0
	5 (rich)	89.8	91.1	92.7	91.9
Gender	Male	74.0	78.3	77.4	79.4
	Female	72.4	76.7	77.2	78.7
Area	Urban	85.9	88.0	88.6	88.0
	Rural	66.4	71.6	70.6	73.7

Source: Susenas 1995, 1997, 1998 and 1999.

Enrolment for the 13 to 15 year age group shows similar patterns. The exception is the poorest quintile. While net enrolment decreased during the crisis, enrolment for this group is much higher than net enrolment since many are still at primary school. Delayed junior secondary enrolment is higher amongst the poor: in the poorest quintile 64 percent of enrolled junior secondary age children actually is in junior secondary school, against 83 percent in the richest quintile.

The second and third quintile achieved the highest increase in senior secondary enrolment, with a 9.1 and 8.6 percent point increase from 1995 to 1999, respectively. The correlation between wealth and enrolment remains nevertheless highest at senior secondary level. The enrolment rate for the richest quintile is 2.5 times as high as for the poorest quintile, and increases almost monotonically with per capita consumption. We see confounding patterns for the different quintiles, which yield an overall increase in enrolment (table 2.4). The poorest three quintiles show strong pre-crisis improvements, a decrease in 1998 (especially for the poor), and a strong recovery in 1999. The two richest quintiles experience continuous improvement in enrolment, which is halted in 1999 as the enrolment rate decreases by less than a percentage point. Note that this dip is actually due to delayed transition from junior to senior secondary school, as overall enrolment amongst 16 to 18 year olds does not decrease for these quintiles.

From 1995 to 1999, the boys-girls gap in enrolment has almost entirely disappeared. Net enrolment rates by gender are given in the second panel of tables 2.2 to 2.4. At primary school there is no difference in boy and girls school enrolment (table 2.2). For both groups enrolment follows the general trend over the period from 1995 to 1999. At the junior secondary level net enrolment is higher for girls. Boys seem to have been affected more by the crisis as net junior secondary enrolment drops by more than a percentage point from 1997 to 1998 (table 2.3). Senior secondary enrolment increase continuously for both groups, albeit faster for girls (table 2.4). In 1995 there is a 1.8 percentage point gap between boys and girls, with 33.5 and 31.7 percent, respectively. By 1999 this has turned around as senior secondary enrolment amongst girls increased to 39.1 percent and for boys to 37.9. Overall, enrolment at secondary school age (i.e., 13 to 18 years) is higher

Table 2.4: Enrolment rates senior secondary school age (16 to 18), from 1995 to 1999, by per capita consumption quintile, gender and area

Net senior secondary enrolment		1995	1997	1998	1999
Consumption quintile	1 (poor)	12.0	15.9	13.2	16.3
	2	19.6	25.5	24.1	28.7
	3	29.1	34.9	34.8	37.7
	4	41.1	45.8	48.6	48.0
	5 (rich)	57.1	59.6	63.5	62.9
Gender	Male	33.5	36.7	37.5	37.9
	Female	31.7	36.5	37.4	39.1
Area	Urban	50.0	54.0	55.5	56.5
	Rural	20.9	24.3	24.2	25.1

Overall enrolment at age 16 to 18		1995	1997	1998	1999
Consumption quintile	1 (poor)	21.6	26.7	24.5	28.1
	2	31.8	37.6	36.2	41.2
	3	41.3	47.2	47.4	51.1
	4	54.2	57.9	60.5	60.5
	5 (rich)	66.7	68.9	72.0	72.2
Gender	Male	46.5	49.3	50.0	50.9
	Female	41.3	46.5	47.4	49.9
Area	Urban	61.3	65.4	66.0	67.3
	Rural	32.2	35.6	36.0	37.9

Source: Susenas 1995, 1997, 1998 and 1999.

for boys, but from 1995 to 1999 this gap narrowed and has practically disappeared in 1999. The effect is most visible for the 16 to 18 age group, for which the boys-girls gap in enrolment narrowed from 5.2 percent point in 1995 to 1 percent point in 1999. There is, however, a difference between those boys and girls that are enrolled. Girls tend to go to a higher education level at a younger age, while delayed enrolment is higher for boys. Girls move faster through the school system and repeat less often.

The third panel in tables 2.2 to 2.4 presents net enrolment rates for urban and rural areas. Net primary school enrolment rates are near universal, and a little higher in urban than in rural areas (table 2.2). In 1998 enrolment amongst primary and junior secondary aged children decreased more in rural than in urban areas. But despite the drop in 1998, primary and junior secondary school enrolment improved from 1995 to 1999 in both urban and rural areas (table 2.3). Senior secondary enrolment increased continuously, with a slight tapering off is found in 1998, especially in rural areas (table 2.4).

2.4 Health

2.4.1 Institutional setting

The public health care system in Indonesia involves a wide network of public health care providers. These public facilities include hospitals (mainly at district level), sub-district health centres (*Puskesmas*), auxiliary health centres (*Puskesmas Pembantu*), mobile health clinics and village maternity homes (*Polindes*). The public health centers offer primary health care services, implement a number of health programmes, and can refer patients to public hospitals. In each village family planning services and maternity care is available through a village midwife programme (*Bidan di Desa*).

There is a considerable private health sector in Indonesia. As we will see below, the private sector covers more than half of all outpatient care utilisation. Private sector consists of private doctors, clinics, hospitals and paramedical services. It is not uncommon that doctors working in public centers also maintain a private practice.

Public health expenditures in the 1997/1998 budget cover about 0.5 percent of GDP (Lanjouw *et al.*, 2002). Just over half of this is attributed to primary health care spending. Per capita private spending on health is considerably higher than public spending. According to expenditure data from the 1998 Susenas health module, aggregate annual household expenditure on health care is more than twice as high as annual public spending.

2.4.2 Health care utilisation and the crisis

The severity of the crisis has undoubtedly affected households' health care expenditures and utilisation. Table 2.5 depicts observed trends in the utilisation of medical services before and during the crisis. The data are based on a series of Susenas household surveys and present utilisation and contact rates of modern health care for a one-month recall period.[11] The contact rate reflects the percentage of people that visited a health care provider at least once, while the utilisation rate reflects the frequency of use (i.e., the contact rate weighted by the number of visits). The table indicates a sharp decrease in the utilisation of modern health care from 1997 to 1998 as the utilisation rate decreased by 26 percent, from 0.19 to 0.14 visits per person. The percentage of people that visited a modern health care provider at least once in the last month decreased from 12.8 to 10.5 percent. The decline in utilisation was largely due to a 33 percent decrease in utilisation of public sector providers. Utilisation of private care also saw a considerable decline, but to a lesser extent with 20 percent. By 1998 the utilisation and contact rate of private facilities (7.8 and 6.1, respectively) exceeded that of public facilities (6.4 and 5.0, respectively). This trend in utilisation is also found in the Indonesian Family Life Survey (e.g. Frankenberg, Thomas and Beegle, 1999).

A breakdown by type of provider is presented in table 2.6 and shows that the decline in public care occurs for the most part at public health clinics. The contact rate at public health clinics decreased by a quarter, from 4.3 percent in 1997 to 3.3 percent in 1998, while 1999 shows a small increase to 3.5 percent. Auxiliary health clinics experienced a similar decline, as the contact rate decreased from 1.7 to 1.0 percent and remained at that level in 1999. Waters, Saadah and Pradhan (2003) attribute this trend to a decline in the supply and quality of health care services at public sector providers. The main cause for this quality deterioration was the growing shortage of medicines, medical equipment and materials with public facilities during the first year of the crisis, especially in rural areas.[12]

Saadah, Pradhan and Surbakti (2000) also argue that the relative strong decrease in public care, compared to private, is not due to price increases. They show that public health clinics were the only providers where user fees (reported by households) did not increase in nominal terms. The cost of care did increase strongly at other facilities,

[11] Modern health care is here defined as public health care providers – hospitals, health clinics (*Puskesmas*), subsidiary health clinics (*Puskesmas pembantu*) village maternity posts (*Polindes*) and integrated health posts (*Posyandu*) – and private providers – hospitals, doctors, clinics and paramedical services. Traditional health care is not included.

[12] See, for example, Ananta and Siregar (1999), Frankenberg, Thomas and Beegle (1999), Frankenberg, Beegle, Thomas and Suriastini (1999), and Knowles, Pernia and Racelis (1999).

especially at hospitals, while use of outpatient care at hospitals remained fairly constant.

From 1998 to 1999 total utilisation of modern health care providers remained the same, but the share of the public sector increased. The contact rate increased to 5.3 percent, and the private contact rate decreased to 5.8 percent. One possible explanation is the JPS health programme, which started during this period.[13]

Both Saadah *et al.* (2000) and Waters *et al.* (2003) note that the pattern of public and private care is very different to other South East Asian countries. For example, in Thailand the use of public care increased during the crisis. Social protection and health insurance schemes were limited in Indonesia, in contrast to Thailand, where such programmes had been expanding in the years prior to the crisis.

Table 2.5: Outpatient utilisation and contact rate, 1995, 1997, 1998 and 1999

	Type of provider	1995	1997	1998	1999
Utilisation rate	Public*	10.9	9.5	6.4	6.9
		[0.14]	[0.13]	[0.09]	[0.10]
	Private†	10.1	9.8	7.8	7.5
		[0.13]	[0.13]	[0.10]	[0.10]
	Modern‡	21.1	19.3	14.2	14.4
		[0.20]	[0.20]	[0.15]	[0.16]
	Traditional	1.6	1.2	0.7	0.6
		[0.05]	[0.04]	[0.02]	[0.03]
Contact rate	Public*	7.0	6.7	5.0	5.3
		[0.08]	[0.08]	[0.06]	[0.07]
	Private†	6.5	6.7	6.1	5.8
		[0.07]	[0.08]	[0.07]	[0.08]
	Modern‡	12.8	12.8	10.5	10.5
		[0.11]	[0.12]	[0.10]	[0.11]
	Traditional	0.7	0.6	0.4	0.4
		[0.02]	[0.02]	[0.01]	[0.01]
Number of observations		873,643	887,266	880,040	864,580

Standard errors in square brackets are adjusted for clustering in survey design.
Source: Susenas 1995, 1997, 1998 and 1999.
* Public hospitals, health clinics, subsidiary health clinics, village maternity posts and integrated health posts.
† Private hospitals, doctors, clinics and paramedical services.
‡ Public and private care. The contact rate for modern care is lower than the sum of the contact rates for public and private care because people that sought both public and private care are counted only once in the aggregate.

[13] Another explanation for the dip in 1998 would be that households postponed preventive care, in anticipation of the health card. But this is unlikely because the JPS interventions had not been announced when the 1998 Susenas survey was conducted.

There is no evidence that nutritional indicators have worsened during the crisis, for example weight for age scores, in 1998 and 1999. This measure is sensitive to short term changes in nutritional status (Saadah *et al.*, 2000; Waters *et al.*, 2003). Self reported illness did increase slightly. However, one needs to be careful interpreting these data, due to measurement error and reporting bias (Strauss and Thomas, 1998).

Utilisation of modern care is strongly correlated with income. Tables 2.7 to 2.9 show utilisation and contact rates at public, private and modern health care providers. During the crisis utilisation has decreased for all quintiles, both in terms of contact rates and utilisation rates. Less people have visited a modern health care provider, and for those that do go the number of visits has decreased over time (table 2.7). The differences between poor and rich have become smaller over time, even during the crisis. In 1999 the utilisation rate for the richest quintile (16.8) is 50 percent higher than for the poorest quintile (11.2). In 1995 modern outpatient care utilisation was 78 percent higher amongst the rich (27.1) compared to the poor (15.2).

Table 2.6: Outpatient contact rate by type of provider, 1995 to 1999

Type of provider	1995	1997	1998	1999
Public hospital	0.64	0.60	0.64	0.59
	[0.015]	[0.017]	[0.017]	[0.019]
Private hospital	0.40	0.41	0.40	0.39
	[0.016]	[0.015]	[0.013]	[0.018]
Private doctor	3.01	3.14	2.84	2.63
	[0.050]	[0.053]	[0.044]	[0.052]
Primary health clinic (*Puskesmas*)	4.66	4.31	3.25	3.46
	[0.065]	[0.069]	[0.049]	[0.057]
Auxiliary health clinic (*Puskesmas Pembantu*)	1.69	1.66	1.01	1.01
	[0.046]	[0.044]	[0.031]	[0.032]
Private clinic	0.42	0.39	0.34	0.31
	[0.020]	[0.020]	[0.015]	[0.016]
Integrated health centre (*Posyandu*)	0.19	0.20	0.12	0.10
	[0.009]	[0.011]	[0.008]	[0.007]
Village maternity home (*Polindes*)	0.38	0.24	0.26	0.40
	[0.017]	[0.013]	[0.015]	[0.015]
Paramedical practitioner (*Petugas*)	2.82	2.93	2.80	2.70
	[0.048]	[0.052]	[0.048]	[0.049]
Traditional care	0.73	0.63	0.43	0.40
	[0.020]	[0.018]	[0.014]	[0.015]
Number of observations	873,647	887,266	880,040	864,580

Standard errors in square brackets are adjusted for clustering in survey design.
Source: Susenas 1995, 1997, 1998 and 1999.

Table 2.7: Utilisation and contact rate modern outpatient care, 1995 to 1999, by per capita consumption quintile, gender and area

Utilisation rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	15.2	14.0	11.3	11.2
	2	18.0	17.3	12.7	12.6
	3	20.7	19.5	14.4	14.7
	4	24.3	21.8	15.9	15.6
	5 (rich)	27.1	24.1	16.8	16.8
Gender	Male	21.3	19.5	14.1	14.2
	Female	20.8	19.2	14.3	14.5
Area	Urban	20.8	19.4	14.5	14.8
	Rural	21.2	19.3	14.0	14.1

Contact rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	9.5	9.6	8.5	8.3
	2	11.3	11.8	9.6	9.5
	3	12.7	13.1	10.7	10.8
	4	14.5	14.3	11.6	11.3
	5 (rich)	16.2	15.5	12.1	12.1
Gender	Male	12.8	12.7	10.3	10.4
	Female	12.9	12.9	10.6	10.7
Area	Urban	13.3	13.2	11.1	11.2
	Rural	12.5	12.6	10.1	10.1

Source: Susenas 1995, 1997, 1998 and 1999.

From 1995 to 1999 the differences in contact rates show a similar pattern. Contact rates amongst the rich remain higher than for the poor, but they have decreased faster during the crisis. Amongst the rich 15.5 percent of the people had visited a modern provider in 1995. By 1998 this had reduced to 12.1 percent. Over this period, the contact rate for the poorest quintile decreased from 9.6 to 8.5 percent.

Use of public care increases with income up to the fourth quintile, and decreases again for the fifth quintile (table 2.8), although from 1995 to 1999 public outpatient utilisation has become more equally distributed. Public utilisation decreased for all quintiles from 1995 to 1998, with the largest dip in 1998, while in 1999 all quintiles increased their use of public care. A notable development in 1998 is the large shift away from public care by the rich, as the contact rate decreased from 6.2 to 4.3 percent. The percentage of people from the poorest quintile that visited a public provider decreased less strongly, from 5.9 to 5.2. In 1998 and 1999 public utilisation and contact rates are lowest for the richest quintile.

Utilisation of private care is distributed very much pro-rich (table 2.9). This pattern has persisted from 1995 to 1999 as utilisation has decreased for all income groups, especially during the first year of the crisis. Unlike public care, no revival is observed in 1999. For the richest quintile the contact rate decreased from 16.1 to 10.7 percent, and for the poor from 3.7 to 3.2 percent.

There is little difference between men and women in terms of utilisation rates. The decreasing pattern in utilisation from 1995 to 1999 is similar for men and women, although utilisation amongst men decreases slightly faster. Before the crisis men had a higher utilisation rate than women (21.3 against 20.8 in 1995), but slightly lower contact rate (12.8 against 12.9). That is, fewer men seek outpatient care, but those that do go more often. This pattern disappears during the crisis in 1998, when men have slightly lower utilisation and contact rates than women (14.1/10.3 against 14.3/10.6, respectively). Another difference is that utilisation of public care is higher amongst women than with men, while private care is used more by men than women. This may reflect outpatient services offered by village midwives and maternity posts.

Table 2.8: Utilisation and contact rate public outpatient care, 1995 to 1999, by per capita consumption quintile, gender and area

Utilisation rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	9.5	8.3	6.6	7.1
	2	10.4	9.5	6.4	6.8
	3	11.4	10.0	6.7	7.4
	4	12.3	10.7	6.7	7.5
	5 (rich)	10.9	9.3	5.8	6.1
Gender	Male	10.9	9.4	6.2	6.6
	Female	11.0	9.6	6.7	7.2
Area	Urban	9.0	8.3	5.8	6.3
	Rural	12.0	10.2	6.8	7.3

Contact rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	6.3	5.9	5.2	5.5
	2	6.9	6.8	5.1	5.4
	3	7.4	7.0	5.3	5.8
	4	7.7	7.4	5.2	5.8
	5 (rich)	6.7	6.2	4.3	4.6
Gender	Male	6.8	6.5	4.8	5.1
	Female	7.2	6.8	5.2	5.6
Area	Urban	6.0	5.9	4.6	4.9
	Rural	7.6	7.1	5.3	5.6

Source: Susenas 1995, 1997, 1998 and 1999.

Table 2.9: Utilisation and contact rate private outpatient care, 1995 to 1999, by per capita consumption quintile, gender and area

Utilisation rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	5.7	5.7	4.7	4.1
	2	7.6	7.9	6.4	5.8
	3	9.3	9.4	7.7	7.3
	4	12.0	11.1	9.2	8.1
	5 (rich)	16.1	14.8	11.0	10.7
Gender	Male	10.4	10.1	8.0	7.6
	Female	9.9	9.5	7.7	7.3
Area	Urban	11.8	11.1	8.8	8.5
	Rural	9.2	9.0	7.2	6.8

Contact rate		1995	1997	1998	1999
Consumption quintile	1 (poor)	3.7	4.0	3.7	3.2
	2	5.0	5.5	5.1	4.6
	3	6.0	6.6	6.0	5.6
	4	7.5	7.5	7.2	6.3
	5 (rich)	10.3	9.8	8.6	8.2
Gender	Male	6.6	6.8	6.2	5.9
	Female	6.4	6.6	6.0	5.7
Area	Urban	7.9	7.7	7.1	6.8
	Rural	5.7	6.1	5.5	5.2

Source: Susenas 1995, 1997, 1998 and 1999.

Utilisation of modern outpatient care is higher in urban areas, while the impact of the crisis was larger in rural areas. Contact rates in urban and rural areas decreased from 13.2 and 12.6 in 1997 to 11.1 and 10.1, respectively. Public utilisation is higher in rural areas, but so is the decrease during the crisis. This follows other reports that the disruption of public care was most severe in rural areas. The private sector is more prominent in urban areas. Public utilisation picked up in 1999, in both rural and urban areas, while private utilisation decreased throughout the period 1995 to 1999.

2.5 Conclusion

The chapter described changes in health care utilisation and school enrolment during the crisis, on the basis of the Susenas household survey. The economic crisis that hit Indonesia in 1997 saw GPD drop by 14 percent in 1998, a strong increase in poverty, rising food prices and sharp budget cuts in social sectors.

Generally, the crisis does not seem to have halted the positive trend in enrolment observed over the period 1995 to 1997, but it did manage to frustrate it for a year. Reduced household spending on education, such as reported by Frankenberg *et al.* (2003), are reflected in aggregate enrolment figures. There is some evidence that children were temporarily taken out of school, with the rural poor affected disproportionately as a result of the crisis. But 1999 saw a full recovery from 1998, bringing enrolment levels higher than they were in 1997. Chapter 5 will argue that the recovery of primary enrolment is due to the JPS scholarship programme. Without the programme, primary enrolment would have decreased further. However, for junior secondary school enrolment the programme can only explain part of the increase.

Increased costs of health care, decreased household income and deteriorating health services were followed by a strong decline in health care utilisation. Utilisation of both public and private care decreased during the crisis for all income groups. Utilisation has decreased stronger for the rich, especially public care.

The main explanation is that quality and supply of public care suffered considerably from the crisis, turning people away from the public sector. This effect has been especially strong amongst the rich. However, there seems no evidence of substitution effects towards the private sector. This suggests other factors are at work. One would be an income effect. Second, quality of private care may also be affected by the crisis and the increased prices of medical supplies.

1999 saw a comeback of the public sector, while utilisation of private care remained constant. Chapter 6 will investigate to what extent this revival is due to the JPS health programme. It appears that the price subsidy that was offered through the health card did indeed increase utilisation of public care. Amongst the poor the health card lead to an increase in the use of health care, while for the non-poor the health cards have only lead to a substitution from private to public care. But the largest effect is due to the budgetary support. The extra resources available to public health facilities under the programme has helped improve quality of care, and increase supply of drugs and materials. However, this supply impulse has only moved the non-poor, as the poor seem only sensitive to the price subsidy.

Chapter 3

The Indonesian Social Safety Net: Programme Design and Benefit Incidence

3.1 Introduction

In an attempt to protect access to health and education for the poor during the crisis, nationwide health and education programmes were introduced in August 1998, as part of the Indonesian Social Safety Net - *Jaring Pengaman Sosial* (JPS). Under the education programme almost 4 million scholarships were made available to primary and secondary school students. The programme followed a partly decentralised allocation process, involving both geographic and community based individual targeting. The size of the scholarship increased with the school level and amounted to about 7 to 18 percent of average per capita household consumption. The scholarships were monthly cash transfers, and students had full discretion on how to use the funds.

The health care intervention followed a few months later, and included both a targeted price subsidy and a public spending component. The price subsidy concerned the revitalisation of the so called health card - *Kartu Sehat*. This card existed before the onset of the crisis, but its use had been negligible. Households that were thought to be most vulnerable to economic shocks were allocated health cards, which entitled all household members to the price subsidy at public health care providers. Health care facilities that provided the subsidised care received extra budgetary support to compensate for the increased demand. However, there was a loose relationship between the utilisation of the health card and the compensation that the health care providers received in return. Compensation was allocated to districts based on the estimated number of households eligible for the health card programme rather than actual utilisation of the health cards. Similar to the education programme, targeting and allocation was decentralised to districts and village communities.

The success of such crisis interventions critically depends on the ability to identify and reach the poor, in particular those that are most vulnerable to the effects of a crisis. Successful targeting requires information on welfare and crisis impact for individual households. Typically, collecting such disaggregated information centrally is costly. The administrative capacity for providing welfare details for each household (for example, a centralised tax administration) is often not available in developing countries like Indonesia. Moreover, short term information regarding the crisis effects for individual households would be hard to retrieve even under a highly developed administrative system. For example, in case of the Indonesian crisis, Skoufias, Suryahadi and Sumarto (2000) find evidence of considerable movement in and out of poverty from 1997 to 1998, hindering accurate targeting of the poor.

The decentralised design of the JPS programmes is meant to deal with this targeting problem. The combination of multi-level geographic and community based targeting provides an alternative infrastructure for gathering and processing information locally, and disseminating this to higher administrative levels. Several authors have argued that a decentralised design can benefit from local knowledge and community participation, on the premise that local communities are more capable of identifying the poor.[1] Not only do local communities have better access to information on targeting criteria, they are also more able to prioritise amongst the set criteria or even formulate new local criteria that better reflect the need for assistance.

However, decentralisation has its weaknesses. Recently, a number of theoretical and empirical studies have investigated the implications and pitfalls of different aspects of decentralisation (e.g. regional political or fiscal autonomy). A main concern is that the benefits of using local knowledge are offset against the loss of control over the allocation process. Decentralised programmes are prone to local elite capture and suffer from classic principal-agent dilemmas (e.g. Bardhan and Mookherjee, 2000 and 2005; Galasso and Ravallion, 2005). In a comprehensive review of the empirical literature on targeting Coady, Grosh and Hoddinott (2004) find that geographic and community based targeting perform above average, but with a large variation between the individual projects.

This chapter deals with the targeting of the two JPS programmes, in light of the decentralised design. The objective is to investigate how the programmes were implemented

[1] See, for example, Alderman (2001 and 2002). Conning and Kevane (2002) provide an extensive review of community based targeting.

in the field and who were the beneficiaries of scholarships and health cards. Were the beneficiaries those people that the programmes intended to reach? Is there evidence of leakage or local capture of benefits by the non-poor? Particular focus will be on the effectiveness of regional targeting policy in contrast to within-district targeting by the allocation committees. Has the central allocation unit been able to identify the regions hit hardest by the crisis? What determines targeting at local level?

Due to a lack of data on the crisis impact, programme managers based geographic targeting on pre-crisis poverty estimates. However, the extent of the crisis varied greatly across regions and was not correlated with pre-crisis poverty. This is also reflected in the geographic targeting criteria for both programmes.

On average, the scholarship are targeted pro-poor, but with high leakage rates to the non-poor. There are also differences between schooling levels. Allocation of primary school scholarships is more pro-poor than at secondary level. Especially at senior secondary level the allocation committees found it difficult to identify the poorest students.

Health card allocation is pro-poor, despite a large number of health cards going to the non-poor. Moreover, health card allocation is more pro-poor than health card utilisation: conditional on ownership, the non-poor use health cards more often. This suggests that not all access barriers to health care are overcome by a user fee waiver. The main deterrent seems to be the opportunity costs of seeking health care. While the more remote areas were targeted because of the lack of access to health care facilities, it is for the same reason that usage rates are low.

The key source of data for this chapter is Indonesia's main socioeconomic survey (*Susenas*). The Susenas is conducted annually on a national scale, collecting information on health, education, socioeconomic background of individuals and households, and detailed information on household expenditures. In 1999 a special JPS module was included. This module provides information on household and individual participation in each of the JPS programmes. The Susenas survey is fielded in February, so the JPS module only reflects programme coverage during the initial 6 months of implementation. The first scholarships and health cards were distributed in the fourth quarter of 1998. By February 1999, the health card programme covered about 11 percent of the population while 5 percent of enrolled children had received a scholarship. In 1999 the core survey included 205,747 households and 864,580 individuals. The number of households included in the JPS module was slightly smaller, at 202,089.

A 1996 village census (*Podes*), provides pre-intervention data on the availability of schools, health care facilities in each village (*desa*) and urban precinct (*kelurahan*) in Indonesia. The Podes includes 66,486 of these communities and can be merged with the Susenas data. A health facility survey, conducted in June 1999 among 3,802 public health clinics and 3,989 village midwives provides information on the amount of JPS funds received and the way in which it has been spent. Finally, I use administrative data on the geographic targeting criteria.

The next two sections in this chapter contain a detailed description of the JPS education (section 3.2) and health (section 3.3) programmes. Each of these sections describes the programme design and who were the main beneficiaries of the programme.

The other sections in this chapter then look into the effectiveness of targeting that underlies the observed benefit incidence. Section 3.4 addresses geographic targeting of both programmes, by comparing the allocation rules with actual poverty and the impact of the crisis across districts. Section 3.5 then investigates the determinants of within-district targeting. Section 3.6 concludes.

3.2 The scholarship programme

3.2.1 Programme design

The JPS scholarship programme was implemented at the start of the 1998/1999 academic year. It was to run for 5 years, financed by the World Bank, the Asian Development Bank and the Government of Indonesia. For the first year the costs amounted to US $ 114 million. The main objective of the programme was to keep enrolment rates for primary and secondary education at pre-crisis levels (Ministry of Education, 1998). The programme aimed to reach 6 percent of enrolled students at primary schools, 17 percent at junior secondary schools, and 10 percent at senior secondary schools. Schools received block grants from an operational assistance fund - *Dana Bantuan Operasional* (DBO) - to maintain quality of education during the crisis.[2]

The size of the scholarships increases with the enrolment level. The scholarships amounted to Rp. 10,000 per month for students in primary school, Rp. 20,000 for junior secondary school, and Rp. 25,000 in senior secondary school. To put these numbers into perspective, average monthly per capita expenditure reported in the 1999 Susenas was Rp. 131,465, while households representing the poorest 20 percent of the population spent Rp. 62,417 per capita per month. For the 1997/1998 school year, monthly expenditures on education per student from the poorest quintile were Rp. 4,881, Rp. 16,123 and Rp. 30,401 (in February 1999 prices) for primary, junior secondary and senior secondary,

[2]The DBO block grants could be used to purchase materials, make repairs, and cover other operational costs.

respectively.[3] Thus, for the poorest households the scholarships are quite significant contributions to monthly income and cover a large part of the expenditures on education.

Through the decentralised design of the programme, scholarships were allocated in three phases. First, the funds were allocated to districts (*kabupaten* and *kota*, based on the level of poverty. At the time of implementation there was no accurate information available on the crisis impact. Therefore a poverty index was constructed based on the 1996 Susenas consumption module (in the rest of the study I will refer to this index as $JPS96$). Poor districts were allocated relatively more scholarships, proportional to the number of enrolled students.

At the district level committees were formed to allocate scholarships to schools. This allocation was based on a prosperity measure for the village or sub-district (*kecamatan*) served by the school, the percentage of IDT eligible villages in the area, and the average school fees paid by students.[4] Both private and public schools were eligible. The district committees were allowed to define additional criteria if they felt this would better reflect local conditions. The prosperity measure was provided by the National Family Planning Coordinating Agency - *Badan Koordinasi Keluarga Berencana Nasional* (BKKBN), and counts the number of poor households based on the so-called *prosperity status*. Under this definition a household classifies as poor if it fails at least one of the following 5 basic needs criteria: (i) households can worship according to faith, (ii) eat basic food twice a day, (iii) have different clothing for school/work and home/leisure activities, (iv) have a floor that is made out of something other than earth, and (v) have access to modern medical care for children or access to modern contraceptive methods. The BKKBN regularly collects this information on a census basis.

Finally, JPS allocation committees were formed at schools to select students for the programme. The committees received guidelines on which allocation criteria to consider. These included the BKKBN prosperity status, single parent and large households, and travel distance from home to school. Another aim was to allocate at least half of the scholarships to girls. Students in primary school grades 1 to 3 were not eligible. The allocation committees could also select children that had already dropped out of school due to the crisis. Continuation of scholarships was conditional on enrolment and passing the grade at the end of the school year. However, no formal conditions were placed on school attendance or how the funds had to be spent.

A distinctive element of the scholarship and block grants programme is the funding

[3] Based on data from an education expenditure module to the 1998 Susenas.

[4] IDT refers to the *Inpres Desa Tertinggal* program, an anti-poverty programme for economically less developed villages. For this program, each village or urban precinct in Indonesia has been classified as either *developed* or *less developed*. This indicator was not used for the primary school poverty ranking.

mechanism itself. The scholarships and grants were transferred directly to local post offices, where the intended beneficiaries could collect the funds. In remote areas, where transportation costs for students are high, post office officials would travel to the schools to disburse the scholarships to the students.

3.2.2 Benefit incidence

Average incidence

By February 1999, at the time that the 1999 Susenas survey was administered, the JPS scholarship programme had not yet reached its intended targets. Table 3.1 shows the allocation of scholarships to enrolled students, by enrollment level. The JPS coverage of enrolled students was 4.0 percent, 8.4 percent and 3.7 percent for the respective enrollment levels. Overall, 5.0 percent of all students in primary and secondary school were covered. Table 3.1 also shows how the JPS programme dwarfs all other scholarship programmes, as it covers about 83 percent of all scholarships.

Table 3.1: Coverage of JPS and non-JPS scholarships (percent of enrolled students, February 1999)

Type	Primary	Junior secondary	Senior secondary	All
Government JPS	4.01	8.42	3.71	4.96
Goverment Non-JPS	0.22	0.76	0.62	0.39
GN-OTA*	0.28	0.39	0.19	0.29
Private sector	0.08	0.25	0.27	0.15
Other	0.12	0.23	0.22	0.16
Total	4.71	10.05	5.02	5.95
N	122,143	41,367	25,522	189,032

Source: Susenas 1999.

* National Foster Parents Movements

Looking at the distribution of the scholarships by per capita expenditure (table 3.2), the pro-poor distribution of JPS scholarships is clear, as is the considerable leakage to students from wealthier households.[5] Amongst students from the poorest 20 percent of the population 7.2, 15.8 and 8.3 percent received a scholarship at primary, and junior and secondary school, respectively. The percentage of scholarship recipients decreases

[5]Some caution is required, as there may be some direct short-term effects on per capita consumption. See van de Walle (2003) for a discussion on assumptions about behavioural responses regarding the effect of public policy on household consumption. Preferably, the analysis should have been based on the pre-intervention per capita consumption level of households. However, this information is not available in the survey. All that is collected is current consumption.

Table 3.2: Distribution of JPS scholarships amongst enrolled children

	Incidence (% of students)	Average odds ratio	Share (%)
Primary			
Quintile 1	7.15	1.78	43.84
Quintile 2	4.78	1.19	26.85
Quintile 3	3.35	0.84	17.27
Quintile 4	1.94	0.48	8.82
Quintile 5	0.92	0.23	3.21
Male	3.70	0.92	47.92
Female	4.36	1.09	52.08
Urban	2.28	0.57	19.96
Rural	4.95	1.23	80.04
All	4.01	1.00	100.00
Junior Secondary			
Quintile 1	15.78	1.87	29.53
Quintile 2	11.55	1.37	27.23
Quintile 3	8.35	0.99	21.63
Quintile 4	5.60	0.67	14.70
Quintile 5	2.84	0.34	6.91
Male	7.89	0.94	47.75
Female	8.96	1.06	52.25
Urban	5.56	0.66	30.18
Rural	10.81	1.28	69.82
All	8.42	1.00	100.00
Senior Secondary			
Quintile 1	8.16	2.20	18.48
Quintile 2	6.49	1.75	25.21
Quintile 3	4.39	1.18	23.18
Quintile 4	2.78	0.75	19.39
Quintile 5	1.63	0.44	13.74
Male	3.43	0.92	46.88
Female	4.00	1.08	53.12
Urban	2.95	0.80	49.83
Rural	4.99	1.35	50.17
All	3.71	1.00	100.00

Number of observations: 122,143 (primary), 41,367 (junior secondary) and 25,522 (senior secondary). Source: Susenas 1999.

gradually for the richer quintiles, with 0.9, 2.8 and 1.6 percent of the richest students being included in the programme, for the respective enrollment levels.

The average odds ratio of receiving a scholarship is given column 2 in table 3.2. This ratio is simply the incidence of benefits for a particular sub-group of the population divided by the average incidence. They reflect the odds of selection into the programme for a child in particular group, relative to the whole population. We see that at all enrolment levels the average odds of receiving a scholarship are the highest for students from the two poorest quintiles. However, average odds ratio's give an incomplete picture of targeting because they do not account for the population structure at different enrolment levels. For example, the poor are typically under-represented at secondary school, so the odds ratio for the first quintile reflect average incidence amongst a smaller group of students than that of the fifth quintile.[6]

The third column in table 3.2 shows the share of scholarships concentrated with the different population groups. These shares offer a different perspective on the allocation, with marked differences between enrolment levels. Whereas the odds ratio for the poor increase with enrolment level, the share of scholarship that is allocated to the poor is greater at primary school at secondary school level. Students from the two poorest quintiles hold 70.7 percent of the primary school scholarships, while 3.2 percent went to the richest quintile. Allocation of scholarships to junior secondary school is also pro-poor, but slightly less than the overall allocation. In contrast, allocation at senior secondary level does not seem to be pro-poor at all. 44.1 percent of the scholarships went to students from the poorest 40 percent, and 13.6 of the scholarships went to students from the richest quintile. In fact, the very poor seem to be underrepresented in the distribution of scholarships at senior secondary level, while the middle quintiles capture most of the benefit.

The concentration curves in the figure 3.1 correspond to the shares reported in table 3.2. The figure shows on the vertical axis the share of scholarships distributed and on the horizontal axis the students ranking in the national distribution of per capita expenditure. It clearly shows the different targeting performance between levels, as the curves never cross. The senior secondary concentration curve does cross with the 45 degree line.

The results in table 3.2 suggest that allocation committees in senior secondary schools find it hard to identify the poorest students in school. One reason could be the relatively small number of children from poor households that enroll at secondary school. For example, the number of senior secondary students from the richest quintile is four

[6] This is also why the average odds for the quintiles do not sum to 5, which they should if the quintiles reflect groups of equal size.

times as high as the number of students from the poorest quintile (32.2 and 7.9 percent, respectively), while in primary school the rich are the smaller group (13.3 and 25.3 percent, respectively). Nevertheless, the number of poor is still greater than the number of scholarships.

The fact that the probability of receiving a scholarship is still higher for the poor in senior secondary school could simply be due to the high number of scholarships allocated to secondary schools, relative to the number of students from the poorest households, as the percentage of students with a scholarship in primary and senior secondary level is about equal (4.0 and 3.7 percent, respectively).

There is a remarkable difference between urban and rural areas. While the impact of the crisis was highest in urban areas, scholarship coverage was much higher in rural areas (6.2 percent against 3.2 percent). This may reflect targeting to the poorest schools, which are located predominantly in rural areas. With regard to the gender of the students, the scholarships have been allocated according to the allocation rules. Table 3.2 shows a slightly higher percentage of girls were reached than boys, in all school levels. This is also reflected in the shares. At all levels girls received just over 50 percent of the scholarships.

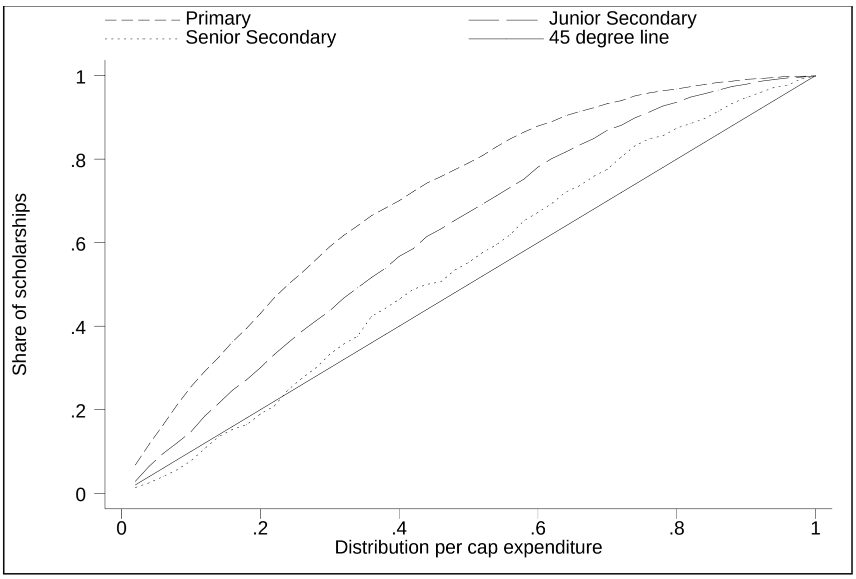

Figure 3.1: Concentration curves for scholarship allocation, by enrolment level.

Marginal incidence

The average incidence analysis above shows how the scholarships are distributed pro-poor. However, this does not tell us who would benefit if the programmes would expand. That is, it says nothing about the benefits of marginal changes to the programmes. But this is something we want to know, since both the health and the education programme were still expanding at the time of the survey. Lanjouw and Ravallion (1999) propose a method of marginal benefit incidence analysis, exploiting regional variation in programme intensity. Their method investigates how marginal changes in the programme will be distributed across different population groups. Denote programme participation by an individual i residing in district k by $y_{iqk} = 1$. Subscript q indicates the per capita consumption quintile. The marginal odds are estimated by regressing the individual programme participation on a constant, c, and the programme coverage in the districts, $\overline{y}_k$, interacted with quintile dummy variables, d_q.[7]

$$y_{iqk} = c + \sum_{q=1}^{5} \theta_q d_q \overline{y}_k + \eta_q + \alpha JPS96_k + \varepsilon_{iqk} \tag{3.1}$$

The coefficients θ_q then reflect the marginal odds ratio, which indicate which quintiles will benefit from a general increase in programme coverage. The quintile specific fixed effects are captured by η_q. District level programme coverage is assumed to be exogenous, as it is determined by the programme design and not targeting of individuals. The regional allocation rule, $JPS96_k$, is included to capture between-district allocation. The marginal effects are estimated using a linear probability model and constraining the θ_q coefficients to sum to 5. Alternatively, $\overline{y}_k$ can be interacted with male/female or urban/rural dummy variables to show marginal benefit incidence by gender or area. In this case the θ_q coefficients will be constrained to sum to 2.

The estimated marginal odds ratios for scholarship allocation show a pro-poor pattern (table 3.3). If the programme were to increase, then the very poor will benefit more than proportionately. For both primary and junior secondary scholarships there is no evidence of early capture by the non-poor. The initial allocation of scholarships is pro-poor, and so will an expansion of the programme be. For senior secondary school this is not the case, although there is also no capture by the rich. Households of the second and third quintiles hold the bulk of the senior secondary scholarships, while the marginal benefits lie with the

[7] While Lanjouw and Ravallion (1999) and Lanjouw *et al.* (2002) estimate the marginal odds using regional aggregated data for different administrative levels, this method can just as well be applied to individual level data (Younger, 2003). Interpretation of the marginal odds parameters remains the same, but the statistical power of the model increases with the number of observations.

second and first quintiles. Note that in early 1999 roughly 30 percent of the population lives below the poverty line.[8] So the observed patterns can hardly be called non-poor. Rather, the results suggest that allocation committees find it hard to distinguish the very poor from the poor in secondary schools.

Table 3.3: Marginal odds ratio of JPS scholarships allocation, 1999

	Primary		Junior Secondary		Senior Secondary	
	θ	[s.e.]	θ	[s.e.]	θ	[s.e.]
Quintile 1	1.20	[0.02]**	1.13	[0.02]**	1.12	[0.03]**
Quintile 2	1.07	[0.02]**	1.21	[0.03]**	1.18	[0.03]**
Quintile 3	1.06	[0.03]**	1.06	[0.03]**	1.04	[0.04]**
Quintile 4	0.90	[0.03]**	0.97	[0.03]**	1.02	[0.04]**
Quintile 5	0.77	[0.04]**	0.63	[0.04]**	0.64	[0.04]**
Male	1.00	[0.01]**	0.96	[0.01]**	0.99	[0.02]**
Female	1.00	[0.01]**	1.04	[0.01]**	1.01	[0.02]**
Urban	0.85	[0.01]**	0.90	[0.02]**	0.95	[0.02]**
Rural	1.15	[0.01]**	1.10	[0.02]**	1.05	[0.02]**

Significance levels: † : 10% $*$: 5% $**$: 1%

Note: see tables 3.12 to 3.14 in appendix 3.A for detailed estimation results.

3.3 The health card programme

3.3.1 Programme design

The JPS health card programme started in the fall of 1998. The health card entitled the owner and family members to free services at public health care providers consisting of (1) outpatient and inpatient care, (2) contraceptives for women of child bearing age, (3) pre-natal care and (4) assistance at birth. This study is limited to the impact of the health card programme on outpatient health care utilisation. The public health care providers where the health cards could be used received budgetary support. These grants were meant to compensate for the expected demand due to the health card and maintain quality of health care. The 1998/1999 budget for JPS health grants to primary health centres (*Puskesmas*) and village midwives (*Bidan di Desa*) amounted to US $ 29 million, financed by the Government of Indonesia and the Asian Development Bank.

The JPS health programme also followed a decentralised design, where the allocation of health cards and funds is delegated to lower administrative levels. The amount of subsidy

[8] For example, Suryahadi *et al.* (2003) calculate a poverty headcount of 27.1 percent in February 1999, based on the Susenas consumption module. See also figure 2.4.

for public health care providers to be distributed across districts, along with the number of health cards to be issued, was determined by the BKKBN headcount per district. The BKKBN prosperity measure has been criticised to be an unsuitable allocation criterion for the JPS, since its components are fairly inflexible and inappropriate for measuring economic shocks or the impact of a crisis. However, at the time of implementation it was the only up to date welfare measure at hand.[9] Furthermore, since national survey data do not allow for estimates below the district level, the BKKBN prosperity measure was also used as allocation rule for both the budgetary support to facilities and health cards to households.

At the district level committees were formed to deal with the allocation of funds to the health clinics and village midwives. This allocation was based on the BKKBN estimate of poor households eligible for a health card in the village or sub-district that is served by each public provider. The transfer was not influenced by the actual services provided to health card owners. The district committee allocated health cards to villages, again based on the BKKBN measure, where the village leaders headed village allocation committees. Along with the health cards they received guidelines on which criteria to use when distributing the health card to households. Besides households that were classified as poor by the BKKBN, the village committees were to consider households that were severely affected by the crisis. The local leaders however maintained a lot of room to distribute health cards according to their own insights. Health cards were usually distributed through local health centres and village midwives.

3.3.2 Benefit Incidence

Average incidence: the missing link between health card allocation and utilisation

The health card programme was already of a substantial magnitude in February 1999 with 10.6 percent of Indonesians reporting that their household was allocated a health card.

Utilisation of outpatient care is higher amongst households that own a health card, especially in case of public services. The utilisation rates provided in table 3.4 indicate that 15.1 percent of the health card owners visited an outpatient provider during a period of 3 months, compared to 12.9 percent for the non-health card owners. Although health card owners tend to choose public providers more often, they do not always use their health

[9] In the second year of the programme (fiscal year 1999/2000) the BKKBN measure for allocation to districts was replaced by a poverty estimate based on household consumption data from the 1999 Susenas, which, by then, provided information on the impact of the crisis.

card. 3.7 out of 10.4 percent of the health card owners report not to use the health card when seeking care at a public provides. Also there are a few instances where a health card is used while the household head reports not to own a health card. Technically, these type of occurrences are possible because ownership information is collected from the household head while utilisation is collected by individual respondents.

Table 3.4: Utilisation of health card 1999 (percent that sought care in past three months)

	Head of household reports to have received a health card	Head of household reports not to have received a health card
Received outpatient care	15.10	12.91
Went to public provider	10.36	6.55
Used health card	6.63	0.14
Did not use health card	3.73	6.41
Went to private provider	4.74	6.36
Number of observations	81,126	741,481

Source: Susenas 1999.

What could explain the weak link between ownership and utilisation? Providers were not reimbursed based on actual services provided, but on the predicted demand. Possibly, the providers themselves selected who they deemed in need for subsidised services and did not always honour the rule that those who could present a health card should be provided free services. Alternatively, rich household may decide to forgo the option of free health care, preferring the higher quality private facilities instead of the public health care center.

Strauss *et al.* (2004) show that at some public health clinics not all services were covered by the health card, but that this can not fully explain the under usage of health cards. Qualitative research by Soelaksono *et al.* (1999) find that at some public facilities, the time allocated to patients with a health card was limited, and that in remote areas the lack of access to the nearest public facility was a possible deterrent to use the health card. They also found indications that patients perceived the care received using a health card to be of lower quality than services and medicines obtained when not using the health card. In addition, the public perception was that treatment at the public clinic was less effective than at private sector.

Health cards are distributed pro-poor. Table 3.5 shows that 18.5 percent of individuals from the poorest quintile had a health card. For people in the second poorest quintile (about half of which are estimated to live below the poverty line at that time) this is 13.7

percent. The allocation shares for ownership and utilisation are presented in column 3 of table 3.5. The poorest 20 percent of the population own 33.7 percent of the health cards. Still there is considerably leakage to the more wealthy households. Considering that about 10 percent of the households received a health card, perfect targeting would imply that all health cards were obtained by the poorest 10 percent of the population. However, the data show that households from the wealthiest 60 percent of the population own about 40 percent of the health cards.

Table 3.5: Distribution of health card allocation and utilisation, 1999

	Incidence (% of Indonesians)	Average odds ratio	Share (%)
Allocation			
Quintile 1	18.45	1.74	33.74
Quintile 2	13.71	1.29	25.68
Quintile 3	10.61	1.00	20.06
Quintile 4	7.09	0.67	13.41
Quintile 5	3.71	0.35	7.10
Male	10.48	0.99	49.28
Female	10.76	1.01	50.72
Urban	7.23	0.68	26.79
Rural	12.82	1.21	73.21
All	10.62	1.00	100.00
Utilisation for outpatient care			
Quintile 1	1.33	1.60	31.30
Quintile 2	1.01	1.22	24.44
Quintile 3	0.84	1.01	20.42
Quintile 4	0.61	0.73	14.89
Quintile 5	0.36	0.43	8.96
Male	0.73	0.88	43.78
Female	0.93	1.12	56.22
Urban	0.62	0.75	29.54
Rural	0.96	1.16	70.46
All	0.83	1.00	100.00

Number of observations: 822,607. Source: Susenas.

Utilisation of health cards for outpatient care is also pro-poor but slightly less so. Those who received benefits were on average wealthier than those who received the card. That means that, conditional on having a health card, the wealthier are more likely to obtain the benefits. Barriers of access to health care, such as lack of information or opportunity costs unabridged by the health card, seem higher for the poor. Even though the rich are more likely to use their health card when they have one, most of the benefits still accrue to the poor. This is because the initial distribution of the health card is distributed pro-poor.

Access to a health card is evenly distributed between men and women, but women tend to use the cards more for outpatient care. These outpatient figures do not reflect the use of health cards for contraception and family planning services. Nevertheless, it could be that the availability of these service under the health card has raised awareness of its usefulness amongst women. Almost three quarters of the health cards is distributed in rural areas. But relative to this distribution, the use of the cards is higher in urban areas. This reflect the differences in access to health care facilities. In urban areas the supply of health services is higher and travel distance to care providers is smaller.

Marginal incidence

The marginal odds ratios for the health card programme is given in table 3.6. Between district allocation is now captured by the district BKKBN headcount. Increasing the overall supply of health cards will increase the share of health cards owned by the poor. But similar to the average incidence results, the marginal change in the utilisation of the health cards is less pro-poor than for allocation. Health card utilisation amongst the poorest changes proportionally with the overall change. The marginal odds are highest for the second and third quintiles. This implies that access barriers to health care for the very poor are not overcome as the programme expands.

Table 3.6: Marginal odds ratio of JPS health card allocation and utilisation, 1999

	Allocation of health cards		Utilisation for outpatient care	
	θ	[s.e.]	θ	[s.e.]
Quintile 1	1.32	[0.01]**	1.01	[0.01]**
Quintile 2	1.15	[0.01]**	1.33	[0.02]**
Quintile 3	1.05	[0.01]**	1.21	[0.02]**
Quintile 4	0.87	[0.01]**	0.89	[0.02]**
Quintile 5	0.60	[0.01]**	0.56	[0.02]**
Male	0.99	[0.00]**	0.95	[0.01]**
Female	1.01	[0.00]**	1.05	[0.01]**
Urban	0.91	[0.00]**	0.98	[0.01]**
Rural	1.09	[0.00]**	1.02	[0.01]**

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Note: see table 3.12 to 3.14 appendix (3.A) for detailed estimation results.

The benefits of budgetary support

The public health care providers were left fairly free in how to utilise the JPS subsidy. The 1999 health facility survey provides some insight in how the JPS health funds have been used. Disbursements to public providers started at the end of 1998. Table 3.7 shows the type of expenses for which the health clinics chose to use the JPS health grants. The spending pattern by public health clinics and village midwives suggests that the JPS budget has been used to support the supply and quality of public care. The largest fraction (41 percent) of JPS health spending concerned medicines and 12 percent was spent on additional materials. In rural areas the share used for medicine is far larger than in urban areas (43 and 38 percent respectively). This reflects the shortage of medicine during the crisis, suggesting that this problem was especially relevant in rural areas (see chapter 2). The village midwives used 38 percent of the funds for medicine and 16 percent for supplies, both urban and rural.

Lanjouw, Pradhan, Saadah, Sayed, and Sparrow (2002) show that up to the crisis the use of public primary health care was higher for the non-poor than for the poor. Households in the third and fourth quintile seem to have been the main beneficiaries of public health spending, as they are the ones that most often visit public health care providers. However, they also show that a general increase in public sector spending will more than proportionately benefit households from the second and third quintiles. Overall, this does suggest that, unlike the health cards, the targeting of the health subsidies will not be geared to the poorest 20 percent of the population.

Table 3.7: Type of expenses for which JPS transfers to health clinics have been used (as percentage of total JPS health program transfers)

	Public health clinic			Village midwife		
	Urban	Rural	All	Urban	Rural	All
Medicine procurement	37.64	43.21	41.40	39.09	38.36	38.44
Medical disposables	14.29	11.56	12.45	16.31	16.49	16.47
Food for in-patients	2.57	1.87	2.10			
Transport costs for referral	5.75	6.75	6.43	3.73	4.09	4.05
Other transport expenses				22.38	20.51	20.72
Birth aids by village midwife	17.05	17.95	17.65			
Contraceptive tools				2.01	3.13	3.01
Tax to Pemda	1.42	1.49	1.47			
Honorarium	2.23	2.04	2.10			
Other	19.05	15.13	16.40	16.48	17.40	17.30
Number of observations	1,319	2,411	3,730	404	3,242	3,646

Source: JPS health facility survey 1999.

3.4 Geographical targeting and crisis impact

How well did the district targeting criteria reflect regional differences in poverty and impact of the crisis?

Several studies have raised concern about the lack of reliable data available for geographic targeting.[10] Given the heterogeneous nature of the crisis, it is likely that criteria for regional targeting misjudged the degree of poverty in the districts, since only pre-crisis information on regional poverty was available. There are two reasons for this. First, the crisis has given rise to large relative price changes, between products (especially food) and across regions.[11] This variation is completely ignored in the targeting process when pre-crisis poverty estimates are applied as allocation rule in 1999. Second, the effects of the crisis varied strongly between regions and were only weakly correlated with the initial level of poverty (Sumarto, Wetterberg and Pritchett, 1998). This heterogeneity of the crisis impact is shown in figure 3.2, which plots 1996 poverty against the change from 1996 to 1999, according to poverty headcount estimates released by the Indonesian Bureau of Statistics (BPS) in 2000. The difference between 1996 and 1999 estimates reflects the impact of the crisis. It indicates the absolute change in the fraction of people that moved into or out of poverty during the crisis. In line with Sumarto *et al.* (1998), there appears to be no correlation between the initial level of poverty and the impact of the crisis.

The BKKBN data are collected at more frequent intervals than the consumption surveys. They can provide fairly up to date information, as far down as the household level. The problem, however, is that the components of the BKKBN classification are inflexible measures and inappropriate for capturing the degree of poverty when faced with severe economic shocks of a crisis.[12]

Table 3.8 is illustrative for the difficulty of capturing the effect of the crisis using pre-crisis data. It shows the ranking of provinces (from low to high) according to the $JPS96$ and BKKBN measures, and the 1999 ($BPS99$) and 1996 ($BPS96$) poverty headcount of

[10] E.g. Ananta and Siregar (1999), Daly and Fane (2002), Dhanani and Islam (2002), and Pritchett, Sumarto and Suryahadi (2002).

[11] E.g. Cameron (1999), Frankenberg, Smith and Thomas (2003), Friedman and Levinsohn (2002).

[12] The main criticism in this respect is that the BKKBN measure is based on fixed assets (type of floor and owning clothes) and non-economic questions regarding religious practices. Sumarto, Suryahadi and Pritchett (2003) place further questions with interregional consistency of the BKKBN measure as the village staff who collect the BKKBN data receive relatively little training, and the figures are vulnerable to manipulation by locale government officials. Using data from a longitudinal survey in 100 villages, Suryahadi, Suharso and Sumarto (1999) show that there is a high degree of mismatch between the BKKBN classification and expenditure based poverty measures. For example, the BKKBN data classify 49 percent of the households in the sample as poor. But according to per capita consumption, only 57 percent of these households rank with the poorest 49 percent of the population.

BPS.[13] The underlying figures are given in table 3.9. The different welfare measures show different levels of poverty. As expected, both the consumption based poverty headcount estimates for 1996 are lower than the one for 1999. If we evaluate welfare by the basic needs criteria of the BKKBN this yields a higher count of deprived households. In itself this is not surprising. What is important is that the rankings are very different. The ranking following the BKKBN and $JPS96$ measures differ from both the levels and changes of poverty, as measured by BPS.

The differences between the welfare measures is further illustrated by a graphical exposition. Figures 3.3 to 3.6 (appendix 3.B) graph the targeting rules against the poverty BPS estimates. Both BKKBN prosperity score and $JPS96$ are strongly positively correlated with the 1999 poverty headcount, but with a lot of variation around the trend. For the BKKBN the correlation seems to be stronger but the variation is also larger. This is not surprising since the BKKBN criteria are not solely based on household consumption. There is no correlation between the change in poverty and $JPS96$. For BKKBN the graph shows a weakly positive trend for the main body of districts. The line is pulled up by a small number of districts that experienced a large increase in poverty. These trends are reflected in the allocation of scholarships (figure 3.7 and 3.8) and health cards (figure 3.9 and 3.10), as reported in the Susenas data.

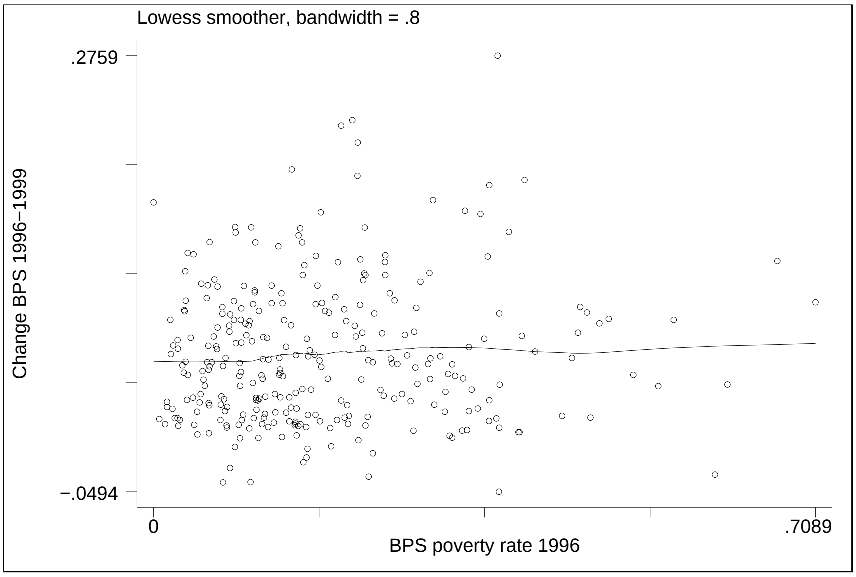

Figure 3.2: Correlation between initial poverty in 1996 and crisis impact on BPS poverty headcount. Locally weighted regression with 0.8 bandwidth. Source: BPS (2000).

[13] Both $JPS96$ and $BPS96$ are based on the 1996 Susenas data, but they differ in methodology for setting poverty lines. The $BPS96$ and $BPS99$ have been constructed in similar fashion, using the Susenas household expenditure surveys. See BPS (2000) for details.

Overall, there is clear evidence of pro-poor targeting. However, the data available to programme managers was not suited to give any information on the crisis impact. There remains a lot of variation around the pro-poor trend, suggesting a high degree of geographic mis-targeting.

Table 3.8: Provinces ranked by geographic allocation rules and BPS poverty estimates (1996 and 1999)

Province	BKKBN 1997	JPS 1996	BPS 1996	BPS 1999	ΔBPS99-96
Aceh	18	16	8	6	11
North-Sumatra	3	17	9	8	14
West-Sumatra	7	7	5	3	13
Riau	10	3	7	4	5
Jambi	4	8	11	17	25
South-Sumatra	12	15	12	14	20
Bengkulu	16	10	14	12	12
Lampung	22	14	21	20	15
Jakarta	2	1	1	1	9
West-Java	6	11	6	11	23
Central-Java	19	20	17	18	18
Yogyakarta	9	12	16	15	21
East-Java	14	19	18	21	19
Bali	1	2	2	2	3
NTB	23	22	23	23	4
NTT	26	24	24	25	22
West-Kalimantan	17	25	20	16	10
Central-Kalimantan	15	18	10	7	6
South-Kalimantan	8	21	3	5	16
East-Kalimantan	5	9	4	13	24
North-Sulawesi	11	13	15	9	1
Central-Sulawesi	20	5	19	19	17
South-Sulawesi	13	4	13	10	8
South-East-Sulawesi	24	6	22	22	2
Maluku	21	23	26	24	7
Irian-Jaya	25	26	25	26	26

See table 3.9 for underlying estimates

Table 3.9: Poverty estimates used for initial JPS allocation in 1996 and BPS poverty estimates (1996 and 1999), by province

Province	BKKBN 1997*	JPS 1996†	BPS 1996‡	BPS 1999‡	ΔBPS99-96
Aceh	51.65	10.99	12.72	14.75	2.03
North-Sumatra	27.56	11.05	13.23	16.74	3.51
West-Sumatra	33.89	8.86	9.84	13.24	3.40
Riau	35.97	8.11	12.62	14.00	1.38
Jambi	29.67	9.30	14.84	26.64	11.80
South-Sumatra	41.27	10.95	15.89	23.53	7.64
Bengkulu	43.22	9.63	16.71	19.79	3.08
Lampung	60.72	10.79	25.59	29.11	3.52
Jakarta	17.32	2.52	2.35	3.99	1.64
West-Java	33.25	10.05	11.06	19.78	8.72
Central-Java	54.30	13.99	21.61	28.46	6.85
Yogyakarta	34.57	10.38	18.43	26.11	7.68
East-Java	42.24	11.91	22.13	29.48	7.35
Bali	0.00	4.30	7.81	8.53	0.72
NTB	62.49	17.80	31.97	32.95	0.98
NTT	82.68	20.82	38.89	46.73	7.84
West-Kalimantan	46.82	22.42	24.21	26.18	1.97
Central-Kalimantan	42.71	11.42	13.50	15.05	1.55
South-Kalimantan	34.03	14.62	8.53	14.37	5.84
East-Kalimantan	32.14	9.45	9.73	20.16	10.43
North-Sulawesi	39.90	10.69	17.94	18.19	0.25
Central-Sulawesi	56.84	8.33	22.30	28.68	6.38
South-Sulawesi	41.53	8.12	16.71	18.32	1.61
South-East-Sulawesi	64.09	8.65	29.23	29.51	0.28
Maluku	60.21	19.77	44.56	46.14	1.58
Irian-Jaya	70.40	31.73	42.28	54.75	12.47
Indonesia	41.98	11.46	17.70	23.43	5.73

Source: * www.bkkbn.go.id, † Ministry of Education (1998), ‡ BPS (2000)

3.5 Community based targeting

3.5.1 Education

What are the key factors that determine targeting at the community level? Table 3.10 reports probit estimates of the factors affecting the probability of an enrolled student being selected for a scholarships. The effects of geographic targeting are captured by district fixed effects, so the estimates can be interpreted as the results from within-district targeting. The table reports marginal effects. The standard errors have been adjusted for the stratified sampling design of the Susenas survey.

The model further includes variables that constitute the main selection criteria for the sub-district and school poverty measures. These are the percentage of BKKBN poor households in the sub-district, and the IDT village classification. The BKKBN variable is based on the official count of households with a *pre-prosperous* or *prosperous I* classification in January 1999. The distance to school for a students is relevant for selection (especially for secondary schools), but is not recorded in the Susenas. However, the 1996 Podes does record the number and type of schools in the village. I will use this information as a proxy for distance to school. Remember that each village should have a primary school, while junior and senior secondary schools typically serve sub-districts and districts.[14]

Individual and household characteristics include age, gender, type of school attending (public or private), per capita expenditure quintile, the five factors that determine BKKBN prosperity status[15], household composition, gender and education of the head of household, the main source of income for the household, living conditions, and a variable that indicates whether or not the student lives in a rural area.

Starting with the personal characteristics, girls are more likely to receive a scholarship, irrespective of the enrollment level. Somewhat surprisingly, attending a public schools increases the probability of selection at all enrolment levels. According to the programme implementation plan no distinction is made between public and private schools. Considering that the model controls for the socioeconomic background of the student, this would suggest that on average public schools have been rated higher (i.e., poorer) on the school poverty ranking, and have relatively more scholarships to distribute.

Turning to household level variables, there is a clear negative relation between per capita expenditure and programme participation. Primary school students from the rich-

[14] Some observations have been lost in merging the Susenas with the Podes and because some districts had not yet implemented the programme.

[15] The real status applied by the BKKBN officials is not recorded in the Susenas survey.

est quintile are 3.2 percentage point less likely to attain a scholarship, relative to students from the poorest quintile. For junior and senior secondary school this is 3.7 and 1.8 percentage point, respectively. Note that these estimates are conditional the geographic allocation criteria. Allocation committees in secondary schools find it hard to distinguish between the poor and the very poor. Nevertheless, the weak pro-poor pattern at senior secondary level does not fully explain the distribution of scholarships, most of which were allocated to the second and third quintile.

The performance of the BKKBN criteria, on the other hand, is a very different story. There is no evidence that the BKKBN criteria have been followed, as most of the criteria do not have a statistically significant effect. Living in a house with a dirt floor or not having different clothes for school/work and home increases the probability of receiving a primary or junior secondary school scholarship. For senior secondary school none of the BKKBN variables are significant.

Other living conditions have been important for eligibility. Access to electricity, clean drinking water and a closed sewer system decrease the eligibility of students, while eligibility is higher for students that live in a bamboo house. This is consistent with findings by Jones *et al.* (2003) that house visits by school teachers were an important part of the local selection process.

Household size and composition have diverse effects for the different enrollment levels. For primary education, an increase in household size decreases the probability of selection, while the household composition variables are not significant. Secondary school students from households with a relatively large share of younger siblings were more likely to be selected for a scholarship.

The characteristics of the head of household have a significant influence on students' prospects of getting a scholarship. Having a female as head of the household increases the probability by 4.6 to 5.7 percentage points. The probability decreases as the educational attainment of the head of household increases, for all enrollment levels.

There is strong evidence that school and community targeting criteria have been used by district selection committees. The variables that are included in the school and sub-district poverty rankings are statistically significant and have the expected sign. Living in an IDT eligible village or a sub-district with a high BKKBN deprivation tally increases the probability of selection.

Table 3.10: Within-district targeting JPS scholarships, probit marginal effects

Variable	Primary	Junior secondary	Senior secondary
Age	0.0083	-0.0016	0.0029
	[0.0006]**	[0.0010]	[0.0014]*
Female	0.0133	0.0131	0.0144
	[0.0022]**	[0.0039]**	[0.0031]**
Public school	0.0124	0.0128	0.0083
	[0.0031]**	[0.0033]**	[0.0027]**
Female head of household	0.0459	0.0565	0.0519
	[0.0057]**	[0.0077]**	[0.0084]**
Education head of household			
None (= reference)			
Primary	-0.0074	-0.0097	-0.0006
	[0.0020]**	[0.0031]**	[0.0032]
Junior secondary	-0.0105	-0.0161	-0.0108
	[0.0028]**	[0.0038]**	[0.0033]**
Senior secondary	-0.0241	-0.0280	-0.0173
	[0.0027]**	[0.0039]**	[0.0032]**
Higher	-0.0269	-0.0366	-0.0152
	[0.0047]**	[0.0050]**	[0.0038]**
Head of household unemployed	0.0199	0.0246	0.0441
	[0.0143]	[0.0178]	[0.0200]*
Ln(household size)	-0.0073	0.0071	-0.0011
	[0.0034]*	[0.0052]	[0.0044]
Household composition			
Share of males age < 6	0.0001	0.0361	0.0172
	[0.0130]	[0.0216]†	[0.0202]
Share of females age < 6	0.0271	0.0701	0.0476
	[0.0131]*	[0.0206]**	[0.0210]*
Share of males age 6-12	0.0129	0.0229	0.0160
	[0.0109]	[0.0150]	[0.0141]
Share of females age 6-12	0.0075	0.0149	0.0134
	[0.0109]	[0.0149]	[0.0142]
Share of males age 13-17	0.0105	0.0410	-0.0018
	[0.0115]	[0.0174]*	[0.0111]
Share of females age 13-17	-0.0181	0.0168	-0.0278
	[0.0120]	[0.0170]	[0.0128]*
Share of males age 18-60 (= reference)			

Continued on next page...

... table 3.10 continued

Variable	Primary	Junior secondary	Senior secondary
Share of females age 18-60	-0.0179	-0.0116	-0.0503
	[0.0135]	[0.0163]	[0.0119]**
Share of males age > 60	0.0162	0.0353	0.0575
	[0.0162]	[0.0238]	[0.0192]**
Share of females age > 60	0.0011	-0.0159	-0.0951
	[0.0169]	[0.0234]	[0.0210]**
Agriculture main source of income	0.0040	0.0031	0.0010
	[0.0023]†	[0.0033]	[0.0034]
Per capita expenditure quintile			
Quintile 1, poorest (= reference)			
Quintile 2	-0.0055	-0.0010	-0.0033
	[0.0024]*	[0.0040]	[0.0041]
Quintile 3	-0.0128	-0.0126	-0.0066
	[0.0025]**	[0.0040]**	[0.0040]†
Quintile 4	-0.0198	-0.0197	-0.0088
	[0.0026]**	[0.0043]**	[0.0041]*
Quintile 5, richest	-0.0320	-0.0368	-0.0176
	[0.0026]**	[0.0044]**	[0.0043]**
BKKBN criteria			
Worship	-0.0014	-0.0081	0.0047
	[0.0036]	[0.0065]	[0.0062]
Food	0.0037	0.0061	-0.0155
	[0.0068]	[0.0102]	[0.0162]
Clothing	-0.0057	-0.0281	-0.0261
	[0.0057]	[0.0123]*	[0.0181]
Floor	-0.0096	-0.0087	-0.0023
	[0.0029]**	[0.0046]†	[0.0049]
Health	0.0005	0.0036	0.0052
	[0.0036]	[0.0055]	[0.0050]
House made out of bamboo	0.0225	0.0258	0.0042
	[0.0036]**	[0.0059]**	[0.0060]
Access to clean drinking water	-0.0052	-0.0083	-0.0095
	[0.0028]†	[0.0037]*	[0.0031]**
Closed sewer	-0.0115	-0.0234	-0.0114
	[0.0027]**	[0.0034]**	[0.0030]**
Access to electricity	-0.0111	-0.0156	-0.0027
	[0.0030]**	[0.0050]**	[0.0056]

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... table 3.10 continued

Variable	Primary	Junior secondary	Senior secondary
Village characteristics			
IDT village	0.0088	0.0084	0.0114
	[0.0030]**	[0.0046]†	[0.0049]*
Rural area	-0.0036	-0.0018	-0.0029
	[0.0041]	[0.0051]	[0.0040]
Primary public school	0.0024	0.0069	0.0023
	[0.0051]	[0.0078]	[0.0060]
Primary private school	0.0044	0.0043	-0.0075
	[0.0027]†	[0.0036]	[0.0031]*
Junior Secondary public school	0.0007	0.0061	0.0010
	[0.0027]	[0.0037]	[0.0030]
Junior Secondary private school	-0.0031	0.0122	0.0057
	[0.0030]	[0.0043]**	[0.0035]
Senior Secondary public school	0.0073	-0.0050	0.0001
	[0.0044]†	[0.0048]	[0.0035]
Senior secondary private school	-0.0031	-0.0075	0.0005
	[0.0036]	[0.0045]†	[0.0036]
Most of inter village traffic by land	-0.0103	-0.0303	0.0099
	[0.0071]	[0.0145]*	[0.0102]
BKKBN poverty rate in subdistrict	0.0410	0.0749	0.0342
	[0.0081]**	[0.0127]**	[0.0115]**
District fixed effects	yes	yes	yes
Observations	55,769	35,909	15,991
Pseudo R-squared	0.19	0.18	0.19

Robust standard errors in brackets.

Significance levels: † : 10% * : 5% ** : 1%

3.5.2 Health

The probit analysis for the health card is conducted at the household level. Table 3.11 shows the determinants for health card allocation (column 1) as well as utilisation conditional on ownership. For the latter, the model is estimated with and without district fixed effects (columns 2 and 3, respectively), since part of the discrepancy between allocation and utilisation of health cards may well be district specific. For example, the supply and quality of public and private health services varies greatly across regions in Indonesia (Lanjouw *et al.*, 2002). This is likely to affect the utilisation of public care and consequently the use health cards. The model specification is similar to the scholarship analysis, except for the individual characteristics and the school proximity variables. Instead, some village level health supply variables are included: the number of public health facilities located in the village, the number of doctors and midwives that live in the village (per 1,000 inhabitants), and a variable indicating the village leader's opinion on accessibility of health facilities in the village.[16]

There are significant negative effects of per capita consumption on the probability of receiving a health card, confirming the pro-poor targeting found in the benefit incidence analysis. Although less prominent, the same holds for the use of the health card conditional upon owning one. The poor tend to use the health cards more often. This indicates that the pro-rich bias found in utilisation is not a direct wealth effect but follows from other background characteristics, which are correlated with wealth.

One such a characteristic is the sector of employment. Being involved in agriculture does not influence within-district targeting. However, households for which agriculture is the main source of income are less likely to use the health card, when district specific effects are ignored. This may indicate that the opportunity costs of time spent at the health clinic or traveling are relatively higher for farm households. Since these households are on average less wealthy than urban households it may be one factor driving the pro-rich bias in utilisation.

Another explanation is the supply and access of health care at village level. The number of auxiliary public clinics negatively affects the probability of receiving a health card. But conditional on ownership the presence of primary and auxiliary public clinics in the village strongly increases the use of health cards for outpatient care. Further, utilisation of health cards is higher in villages where the village leader views health care facilities to be easy or very easy to reach. While remote and less wealthy areas with little access to health care receive priority in the targeting process, the direct and indirect costs of using the cards are relatively high.

On the other hand, the probability of selection increases as the number of doctors and midwives living in the village increases. Since it is the medical staff of local clinics that actually distribute the health cards to households, this might reflect the importance of informal contacts within the village for participation in social programmes.

The probit results confirm that health cards have been awarded to households based on health status. The official allocation rules require health cards to be distributed to the poor, irrespective of their health status. But the clearly positive effect on the vari-

[16]The Podes survey asks village leaders whether the closest public health clinics are (i) very easy, (ii) easy, (iii) difficult or (iv) very difficult to reach by the majority of the village population.

able measuring whether any household member experienced an illness in the past month indicates that often health cards were given based on acute need. For those who get sick and do not own a health card, it is still possible to get a health card after seeking medical care (Soelaksono *et al.*, 1999). Not surprisingly, the propensity of using a health card also increases strongly when a household member falls ill.

Turning to household composition effects, the results show that (conditional on per capita consumption) households with a relatively large share of children and elderly have a higher probability of receiving and using a health card. Conditional on household composition, household size is of little importance for targeting.

Household headed by females have a significantly higher chance of receiving a health card. Education of the head also plays an important role. Higher education has a negative effect on the probability of receiving a health card. But controlling for other household variables, the characteristics of the head of household seem not to be correlated with utilisation of health cards.

The results confirm that the BKKBN prosperity status variables have been used to decide the allocation of health cards. Floor material is a strong predictor for health card ownership. Those with an earth floor have a higher chance of receiving a health card, but a lower probability of actually using it for outpatient care. Access to modern care increases the chance of receiving a health card and, conditional on ownership, also increases the chance of using it. Owning different sets of clothing for work and leisure decreases the probability of owning and using a health card. Being able to worship according to faith increases the probability of using a health card.

There is clear evidence that living conditions was one of the factors that took priority in the local targeting process. Having access to electricity and clean drinking water, a closed sewer and living in a house not made out of bamboo all decrease the probability of receiving a health card.

Official targeting criteria like the IDT village indicator and the sub-district BKKBN basic needs measure all perform as expected, increasing the probability of receiving a health card. Interestingly, the BKKBN measure has a strong negative effect on utilisation. This may indicate a quality deterioration effect. The quality of care provided by health facilities may decrease as the pressure of the programme increases. This can negatively affect the households willingness to use the cards.

Table 3.11: Within-district targeting JPS health card to households, and determinants of utilisation for outpatient treatment, probit marginal effects

Variable	Health card allocation	Health card use for outpatient care	
	(1)	(2)	(3)
	(District fixed effects)		
Female head of household	0.0215	0.0136	0.0165
	[0.0025]**	[0.0111]	[0.0116]
Education head of household			
None (= reference)			
Primary	-0.0063	0.0016	-0.0014
	[0.0015]**	[0.0072]	[0.0080]
Junior secondary	-0.0166	0.0017	-0.0009
	[0.0019]**	[0.0120]	[0.0128]
Senior secondary	-0.0272	-0.0036	0.0010
	[0.0020]**	[0.0132]	[0.0142]
Higher	-0.0339	-0.0173	-0.0153
	[0.0030]**	[0.0280]	[0.0296]
Head of household unemployed	0.0080	-0.0359	-0.0214
	[0.0069]	[0.0279]	[0.0322]
Member of household ill last month	0.0123	0.2091	0.2197
	[0.0015]**	[0.0080]**	[0.0086]**
Ln(household size)	-0.0003	0.0058	0.0121
	[0.0018]	[0.0095]	[0.0101]
Household composition			
Share of males age < 6	0.0440	0.0833	0.0778
	[0.0062]**	[0.0326]*	[0.0344]*
Share of females age < 6	0.0388	0.1234	0.1046
	[0.0065]**	[0.0333]**	[0.0356]**
Share of males age 6-12	0.0114	0.0425	0.0306
	[0.0053]*	[0.0284]	[0.0301]
Share of females age 6-12	0.0159	0.0566	0.0365
	[0.0055]**	[0.0286]*	[0.0293]
Share of males age 13-17	0.0144	-0.0384	-0.0443
	[0.0058]*	[0.0343]	[0.0359]
Share of females age 13-17	-0.0001	-0.0443	-0.0354
	[0.0061]	[0.0343]	[0.0368]
Share of males age 18-60 (= reference)			
Share of females age 18-60	0.0053	0.0369	0.0570

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... table 3.11 continued

Variable	Health card allocation (1)	Health card use for outpatient care (2)	(3)
	[0.0048]	[0.0279]	[0.0300]†
Share of males age > 60	0.0136	0.1096	0.1061
	[0.0051]**	[0.0262]**	[0.0281]**
Share of females age > 60	0.0099	0.0609	0.0681
	[0.0050]†	[0.0272]*	[0.0289]*
Agriculture main source of income	-0.0019	-0.0103	-0.0138
	[0.0017]	[0.0077]	[0.0083]†
Per capita expenditure quintile			
Quintile 1, poorest (= reference)			
Quintile 2	-0.0117	-0.0083	-0.0132
	[0.0019]**	[0.0086]	[0.0092]
Quintile 3	-0.0193	-0.0160	-0.0194
	[0.0021]**	[0.0098]	[0.0103]†
Quintile 4	-0.0311	-0.0279	-0.0345
	[0.0021]**	[0.0110]*	[0.0113]**
Quintile 5, richest	-0.0492	-0.0361	-0.0475
	[0.0024]**	[0.0139]**	[0.0138]**
BKKBN criteria			
Worship	-0.0011	0.0217	0.0286
	[0.0029]	[0.0111]†	[0.0118]*
Food	-0.0081	0.0194	-0.0106
	[0.0065]	[0.0203]	[0.0256]
Clothing	-0.0086	-0.0440	-0.0489
	[0.0046]†	[0.0160]**	[0.0183]**
Floor	-0.0292	0.0279	0.0258
	[0.0025]**	[0.0079]**	[0.0085]**
Health	0.0169	0.0786	0.0856
	[0.0022]**	[0.0089]**	[0.0095]**
House made out of bamboo	0.0359	0.0139	0.0090
	[0.0028]**	[0.0092]	[0.0096]
Access to clean drinking water	-0.0057	0.0086	0.0152
	[0.0025]*	[0.0114]	[0.0119]
Closed sewer	-0.0218	-0.0152	-0.0021
	[0.0020]**	[0.0096]	[0.0103]
Access to electricity	-0.0063	-0.0050	-0.0214
	[0.0027]*	[0.0099]	[0.0108]*

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... table 3.11 continued

Variable	Health card allocation	Health card use for outpatient care	
	(1)	(2)	(3)
Village characteristics			
IDT village	0.0102	-0.0042	0.0235
	[0.0032]**	[0.0112]	[0.0115]*
Rural area	0.0025	0.0129	0.0018
	[0.0035]	[0.0143]	[0.0133]
Nr. of primary health clinics	-0.0001	0.0233	0.0262
	[0.0028]	[0.0116]*	[0.0120]*
Nr. of auxiliary health clinics	-0.0095	0.0308	0.0392
	[0.0023]**	[0.0090]**	[0.0092]**
Nr. of integrated health centres	-0.0033	0.0005	-0.0191
	[0.0027]	[0.0107]	[0.0109]†
Nr. of doctors per 1,000 inhabitants	0.0087	0.0049	-0.0002
	[0.0031]**	[0.0111]	[0.0108]
Nr. of midwifes per 1,000 inhabitants	0.0127	0.0148	0.0342
	[0.0031]**	[0.0115]	[0.0139]*
Health facilities easy to reach	0.0035	0.0273	0.0545
	[0.0052]	[0.0177]	[0.0178]**
Most of inter village traffic by land	0.0098	-0.0819	-0.0151
	[0.0070]	[0.0450]†	[0.0345]
BKKBN poverty rate in subdistrict	0.0448	-0.0794	0.0148
	[0.0087]**	[0.0323]*	[0.0223]
District fixed effects	yes	yes	no
Observations	188,451	18,771	18,771
Pseudo R-squared	0.19	0.15	0.09

Robust standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

3.6 Conclusion

This chapter discussed the design and implementation of the health and education safety net programmes that were introduced in Indonesia in August 1998, as response to the economic crisis. Under the education programme almost 4 million scholarships were made available to primary and secondary school students. The scholarships were cash transfers and the amount increased with enrolment level. The health programme consisted of a health cost waiver scheme for households, in the form of a health card, and budgetary support to public health care facilities. The health card programme has a weak link between the delivery of services to health card owners and the financial compensation. Service providers were reimbursed using a lump sum transfer based on the estimated number of poor households in their area of influence. As a result, serving a health card owner did not result in a direct financial reward to the service provider. Both programmes were targeted to the poor following a partly decentralised allocation process, involving both geographic and community based individual targeting.

The programmes have been implemented at the remarkable speed. By February 1999 approximately 22 million people (about 11 percent of Indonesians) lived in households that received a health card, and 2.1 million children aged 10 to 18 (about 5 percent) had received a scholarship. The decentralised programme design may well have facilitated this swift reaction, by relying on existing administrative and operational infrastructure within the districts. However, at such short notice there was no reliable data on the impact of the crisis across districts. Geographic targeting criteria were therefore based on pre-crisis poverty estimates, which reflect the actual level of poverty to some extent but do not capture the impact of the crisis. There appears to be no correlation between the initial level of poverty and the impact of the crisis. Moreover, applying the pre-crisis poverty estimates as allocation rule in 1999 is implicitly assuming that relative prices have not changed.

Targeting of scholarships differed strongly between enrolment levels. Targeting was pro-poor at primary and junior secondary level, but there was also a lot of leakage to wealthier groups. For senior secondary school the scholarships were not allocated pro-poor at all, but instead distributed quite evenly. It appears that allocation committees found it very difficult to identify the poorest students in senior secondary schools.

There is clear evidence that the health card programme was pro-poor in the sense that the poor had a higher probability of receiving a health card and using it to obtain free health services, presumably making them healthier. However, despite pro-poor targeting, a considerable number of health cards went to households in the richer quintiles. Service providers also seem to have distributed health cards based on health status and to patients that show up to ask for services.

A notable finding is that some health card owners did not use their health card when obtaining care from public service providers. It seems like several factors are in play. The particular design resulted in a discrepancy between health card ownership and utilisation. High rejection rates could follow from the delays in the lump sum transfers made to the providers. Patients could also perceive health care obtained using a health card to be inferior to the service and medicines given to patients who pay the normal user fees.

Utilisation of services is less pro-poor than ownership. Conditional on ownership, the rich have a higher propensity to use their health card, suggesting that access barriers to health care are not fully overcome by a price subsidy. The direct and indirect costs of using the health card are relatively higher in the more remote, and rural villages with little access to public health care providers.

3.A Supplementary tables

Table 3.12: Marginal benefit incidence analysis, by per capita expenditure quintile (linear probability estimates)

	Scholarships						Health cards			
	Primary		Junior secondary		Senior secondary		Allocation		Utilisation	
	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]
Marginal odds ratio (θ) [1]										
Quintile 1	1.204	[0.016]**	1.128	[0.022]**	1.120	[0.028]**	1.323	[0.006]**	1.011	[0.009]**
Quintile 2	1.066	[0.021]**	1.205	[0.026]**	1.182	[0.033]**	1.149	[0.006]**	1.326	[0.016]**
Quintile 3	1.060	[0.026]**	1.058	[0.031]**	1.039	[0.039]**	1.053	[0.007]**	1.208	[0.019]**
Quintile 4	0.900	[0.029]**	0.975	[0.033]**	1.015	[0.040]**	0.872	[0.007]**	0.891	[0.021]**
Quintile 5	0.769	[0.038]**	0.634	[0.037]**	0.644	[0.040]**	0.603	[0.008]**	0.564	[0.023]**
Quintile dummy variables										
Quintile 1 (= reference)										
Quintile 2	-0.003	[0.002]**	-0.024	[0.006]**	-0.009	[0.006]	-0.007	[0.001]**	-0.004	[0.0004]**
Quintile 3	-0.012	[0.002]**	-0.030	[0.006]**	-0.013	[0.006]*	-0.017	[0.001]**	-0.004	[0.0004]**
Quintile 4	-0.014	[0.002]**	-0.037	[0.006]**	-0.020	[0.005]**	-0.022	[0.001]**	-0.003	[0.0004]**
Quintile 5	-0.018	[0.002]**	-0.036	[0.006]**	-0.020	[0.005]**	-0.027	[0.001]**	-0.003	[0.0004]**
$JPS96$	-0.091	[0.008]**	-0.144	[0.017]**	-0.060	[0.016]**				
BKKBN 1997							-0.051	[0.001]**	-0.004	[0.0005]**
Constant	0.016	[0.002]**	0.040	[0.0048]**	0.022	[0.005]**	0.033	[0.001]**	0.004	[0.0004]**
Observations	126,080		42,271		25,856		842,365		842,365	
Root mean square error	0.189		0.272		0.188		0.279		0.095	

Significance levels: † : 10% $*$: 5% $**$: 1%

[1] The θ coefficients are constrained to sum to 5.

Table 3.13: Marginal benefit incidence analysis, by gender (linear probability estimates)

	Scholarships						Health cards			
	Primary		Junior secondary		Senior secondary		Allocation		Utilisation	
	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]
Marginal odds ratio (θ) [1]										
Male	1.002	[0.010]**	0.961	[0.013]**	0.988	[0.017]**	0.994	[0.003]**	0.947	[0.007]**
Female	0.998	[0.010]**	1.039	[0.013]**	1.012	[0.017]**	1.006	[0.003]**	1.053	[0.007]**
Gender dummy variables										
Male (= reference)										
Female	0.006	[0.001]**	0.002	[0.004]	0.007	[0.003]*	0.0002	[0.001]	0.001	[0.0002]**
$JPS96$	0.000	[0.006]	0.003	[0.015]	0.001	[0.015]				
BKKBN 1997							0.00004	[0.001]	0.00001	[0.0005]
Constant	-0.003	[0.001]**	-0.001	[0.003]	-0.004	[0.002]*	-0.0001	[0.001]	-0.0004	[0.0003]
Observations	126,157		42,321		25,940		844,147		844,147	
Root mean square error	0.200		0.274		0.189		0.282		0.095	

Significance levels: † : 10% $*$: 5% $**$: 1%

[1] The θ coefficients are constrained to sum to 2.

Table 3.14: Marginal benefit incidence analysis, by urban-rural area (linear probability estimates)

	Scholarships						Health cards			
	Primary		Junior secondary		Senior secondary		Allocation		Utilisation	
	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]	Coef.	[s.e.]
Marginal odds ratio (θ) [1]										
Urban	0.853	[0.013]**	0.902	[0.015]**	0.953	[0.018]**	0.907	[0.003]**	0.981	[0.007]**
Rural	1.147	[0.013]**	1.100	[0.015]**	1.047	[0.018]**	1.093	[0.003]**	1.019	[0.007]**
Area dummy variables										
Urban (= reference)										
Rural	-0.001	[0.002]	0.0002	[0.004]	0.001	[0.003]	0.003	[0.001]**	0.001	[0.0003]**
$JPS96$	-0.063	[0.008]**	-1.072	[0.018]**	-0.019	[0.017]				
BKKBN 1997							-0.021	[0.001]**	-0.001	[0.0005]*
Constant	0.005	[0.001]**	0.004	[0.003]	0.001	[0.002]	0.002	[0.001]*	-0.0001	[0.0003]
Observations	126,157		42,321		25,940		844,147		844,147	
Root mean square error	0.200		0.273		0.189		0.281		0.095	

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

[1] The θ coefficients are constrained to sum to 2.

3.B Supplementary figures

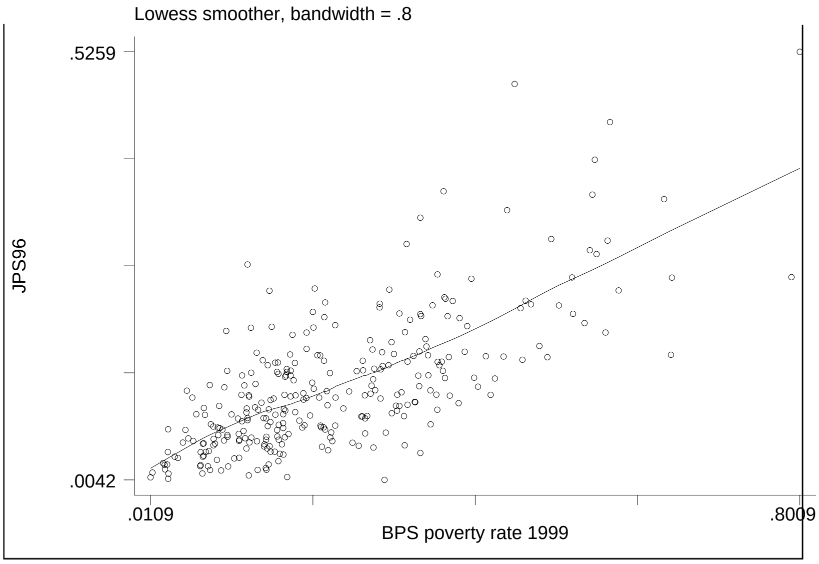

Figure 3.3: Correlation between $JPS96$ and BPS 1999 poverty rate.

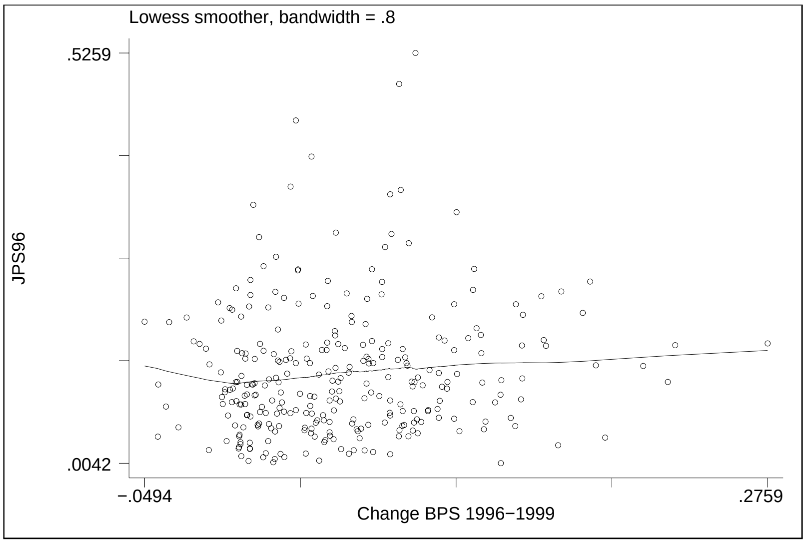

Figure 3.4: Correlation between $JPS96$ and crisis impact on BPS poverty rate.

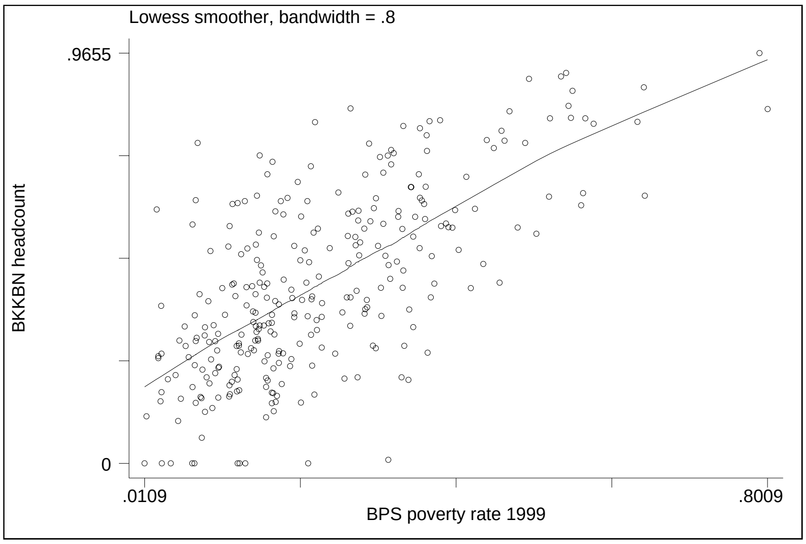

Figure 3.5: Correlation between BKKBN headcount December 1997 and BPS 1999 poverty rate.

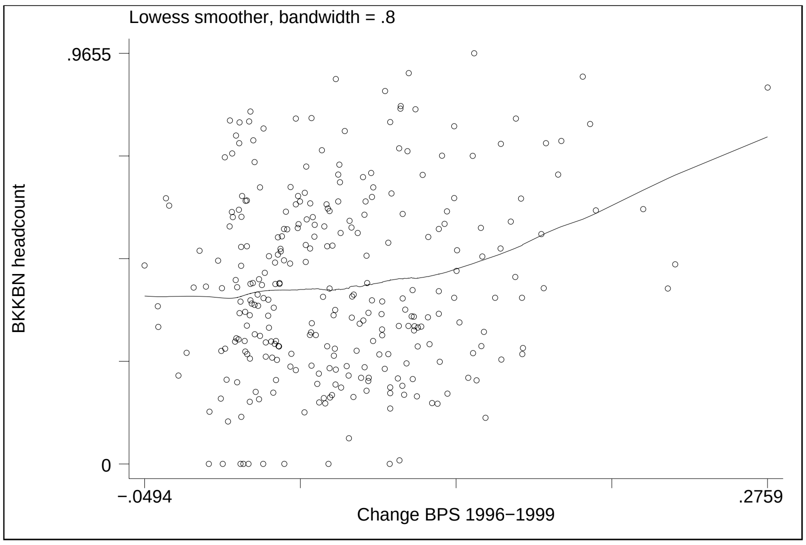

Figure 3.6: Correlation between BKKBN headcount December 1997 and crisis impact on BPS poverty rate.

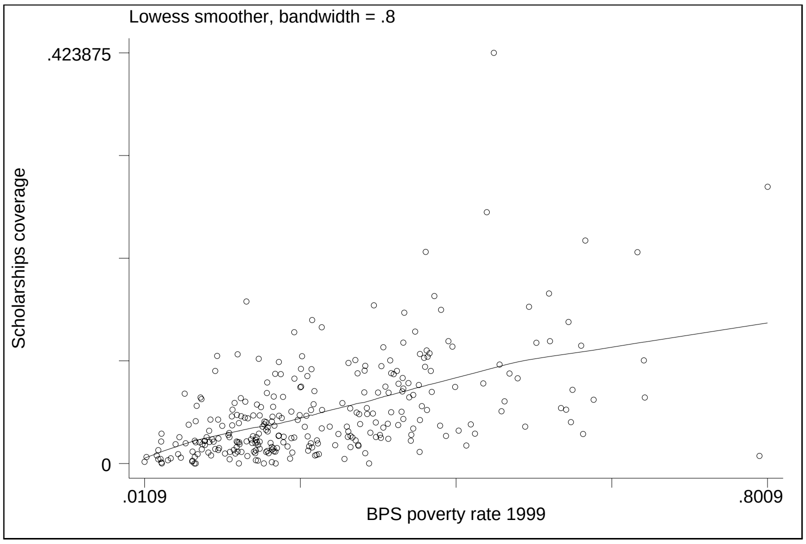

Figure 3.7: Correlation between scholarship coverage and BPS 1999 poverty rate.

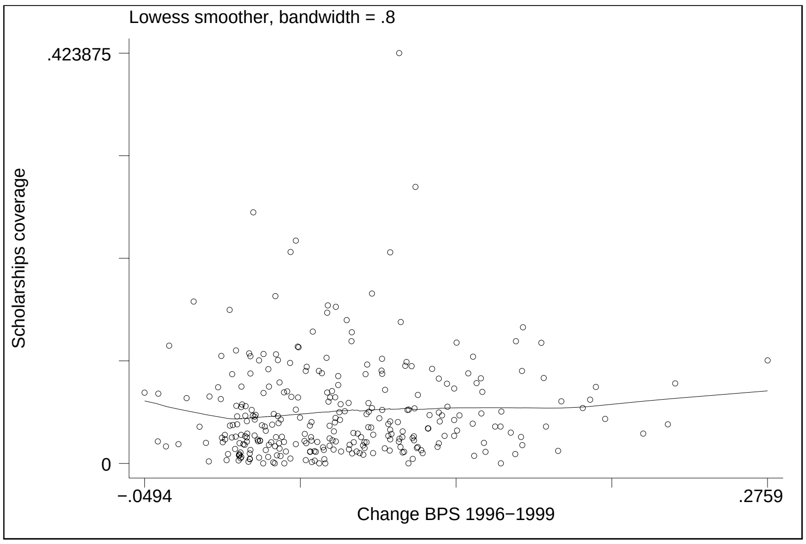

Figure 3.8: Correlation between scholarship coverage and crisis impact on BPS poverty rate.

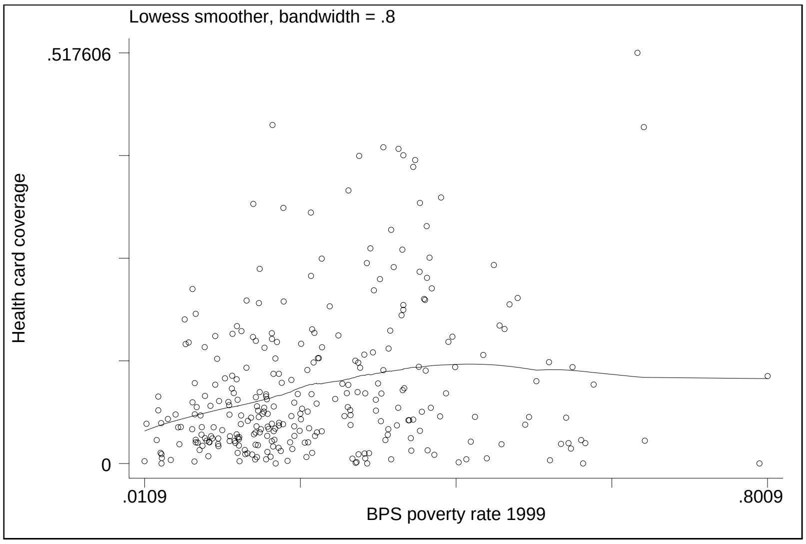

Figure 3.9: Correlation between health card coverage and BPS 1999 poverty rate.

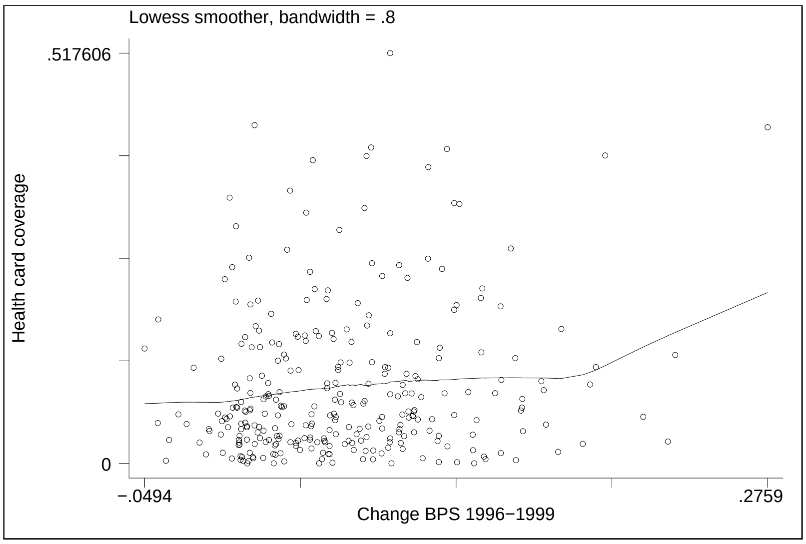

Figure 3.10: Correlation between health card coverage and crisis impact on BPS poverty rate.

Chapter 4

Simulation Based Benefit Incidence Analysis

4.1 Introduction

Decentralising public service delivery to local communities has become a growing trend in the past decade (World Bank, 2004). A prominent argument is that, given the right institutional incentives, delegating part of the responsibility to lower political and administrative levels will improve effectiveness of service delivery to the poor. Evidence of the effectiveness of decentralisation is ambiguous, however. On the one hand it is recognised that local authorities may have superior information on local needs and preferences (e.g. Alderman, 2002). On the other, decentralisation may increase inequality due to local elite capture or lack of accountability (e.g. Lanjouw and Ravallion, 1999; Galasso and Ravallion, 2005). Even if communities use their informational advantage to the benefit of the poor, local pro-poor targeting may be frustrated by ineffective regional targeting by the central government (e.g. Alderman, 2001). In such a decentralised setting a question that remains is how changes in public policy at a central level affect the targeting of services to the poor. How do we measure the marginal effects of regional targeting on the distribution of benefits from public policy, and how can we disentangle this from the effects of local targeting?

The recent literature on benefit incidence proposes a number of methods for marginal benefit incidence analysis.[1] These methods supplement traditional average benefit incidence in that they investigate distributional effects of marginal changes in social service delivery. However, these methods do not shed light on the underlying factors that drive

[1] For a discussion on average and marginal benefit incidence see, for example, Younger (2003) and van de Walle (2004).

the observed marginal incidence. As has been pointed out by others, these methods can not discern whether observed differences are due to geographic targeting, local policy decisions or behaviour and characteristics of households.

Decomposing targeting performance into geographic and local specific targeting is not straightforward. Decomposable indices such as a concentration index or targeting differential are informative measures on socioeconomic inequality in the use of services.[2] But these indices do not show how the full distribution of public service utilisation over the population changes. In this chapter I apply a micro-simulation based approach for dynamic benefit incidence analysis to the JPS scholarship and health card programmes. This method builds on an extension to the Oaxaca-Blinder decomposition method, proposed by Bourguignon, Fournier and Gurgand (2001).

From 1999 to 2002 both the JPS scholarship and health card programmes have expanded. Both programmes were targeted pro-poor, following a decentralised design that involved geographic and community based targeting. However, the changes in the distribution of benefits from both programmes show quite different patterns. The poor have been the main beneficiaries of an increase in scholarships, whereas the expansion of the health card does not show a pro-poor pattern. An important aspect of these programmes is that the geographic targeting rules were altered after 1999, when more accurate information on regional poverty became available. The main question I address here is to what extent the distributional outcome of the programme's expansion is a result of geographical targeting by the central allocation unit in Jakarta, or whether this was mainly determined at the community level.

The results show how the simulations facilitate understanding and interpretation of conventional marginal benefit incidence results. For the scholarship programme the marginal incidence in itself provides misleading policy advice, as it suggests that programme expansion would benefit the poor. The decompositions, however, show that pro-poor marginal incidence is driven by improved local and geographical targeting over time. Expanding the programme without simultaneously improving the targeting process would in fact increase leakage to the non-poor. For the health card programme, the decomposition results are not conflicting with marginal incidence results. Instead, they highlights which targeting instruments would be most effective in reallocating health cards to the poor.

The next section provides a theoretical framework for the analysis. It provides a simple model describing the decentralised targeting process. Section 3 provides a dynamic benefit incidence analysis applying some commonly used methods. Section 4 then continues by

[2]See, for example, Bidani and Ravallion (1997), Ravallion (2000), and Wagstaff, van Doorslaer, Watanabe (2003).

exploring how the effects of central and local policy instruments can be disentangled, using a simulation based decomposition approach. The results a given in section 5 and section 6 concludes.

4.2 A simple model of decentralised targeting

This section illustrates the targeting problem and the determinants driving the observed distributional outcomes with a simple model.

Consider a social programme where targeting is fully decentralised: funds are centrally allocated to district communities, which, in turn, are responsible for targeting households. The transfer, y_{ik}, that household i, residing in district k, receives from the programme is thus determined by a two-stage targeting process. First, it depends on the outcome of the geographical targeting process, in which district k receives amount s_k of funds.[3] Second, it depends on how the local officials distribute this s_k amongst the households in the districts.

Let us start the exposition with the district based targeting phase, taking s_k as given. This assumes that the communities have no influence on the allocation decision by the centre. This is a plausible setting for the JPS programmes, where first stage targeting was a purely administrative exercise using data exogenous to the programme.[4] It is further assumed that the centre has no direct influence on within-district targeting.

The community members in charge of local targeting do not have full information about the households circumstances. Households are described by a set of characteristics x^*_{ik}, but some of these characteristics, η_{ik}, remain unobserved (although the distribution of η_{ik} is assumed to be known). Thus $x^*_{ik} = (x_{ik}, \eta_{ik})$, where x_{ik} is observed information. This introduces some local uncertainty. The decentralised targeting design is justified as long as communities are more able to reduce this uncertainty and the local costs of gathering the (observed) information x_{ik} is smaller, compared to a fully centralised programme.

The targeting problem of local programme managers is to maximise the utility of the N_k households within the district, subject to the local programme budget constraint. Denote the utility gain from the benefits for a household by $U_{ik}(y_{ik}, x^*_{ik})$, which is assumed

[3] Note that the JPS introduced multilpe layers of geographic targeting, with targeting to districts, sub-districts, and schools.

[4] For many programs exogeneity of geographic targeting is not a credible assumption. This can be the case when, for example, geographic targeting is based on data that is collected by communities themselves. It is also not uncommon that political decision making regarding social policy is influenced by local pressure groups and lobbying of community officials. See for example Galasso and Ravallion (2005), who question the exogeneity of geographic targeting and discuss the implications for empirical analysis.

to be concave and strictly increasing in y_{ik}. However, targeting implies that from the perspective of programme managers, the welfare of some households receives priority over others. These priorities are expressed by welfare, or *Pareto*, weights λ. These weights can reflect a complex variety of factors, such as the targeting criteria communicated through the programme guidelines or locally formulated criteria. Political economy factors also influence the welfare weights if the targeting process is sensitive to political empowerment or capture by some population groups. This effect manifests itself through the political, economic or demographic environment in the districts.[5] The welfare weights will then be a function of household and district characteristics (x^*_{ik} and w_k, respectively), and the local budget (s_k).

The local maximisation problem then becomes

$$\max_{y_{ik}} \sum_{i=1}^{N_k} E_{\eta_{ik}} \left[U_{ik} \left(y_{ik}, x^*_{ik} \right) \lambda \left(x^*_{ik}, s_k, w_k \right) \mid x_{ik} \right] \tag{4.1}$$

$$\text{s.t.} \sum_{i=1}^{N_k} y_{ik} = s_k,\ y_{ik} \geq 0 \quad \forall i, k \tag{4.2}$$

with the solution

$$y^*_{ik} = H \left[s_k, x^*_{ik}, \eta_{ik}, \lambda \left(x^*_{ik}, s_k, w_k \right) \right] \tag{4.3}$$

Note that this exposition is simply a more general formulation of the model described in Galasso and Ravallion (2005), in that their model maximizes aggregate (per capita) welfare functions explicitly defined for the poor and the non-poor.

In similar vein, a targeting problem can be described for the centre. First of all, this depends on the centre's view of regional priorities (or fairness, if you will). Should two equally poor people have the same probability of receiving a benefit independent of where they live? Or do some regions require priority over others? A second issue regards the centre's information constraints. Geographic targeting crucially depends on available data for regional welfare. The center also does not have full knowledge of local targeting criteria (the districts' set of Pareto weights). That is, it does not exactly know how lower operational and administrative units will implement the programme. Taking into account the expected allocation behaviour of communities, the available data on regional welfare, and some degree of uncertainty associated with lack of information, solving the centre's maximisation problem will yield some pattern of regional programme intensity $s^*_k = \alpha_k S$, where $S = \sum_{k=1}^{K} s_k$ is the national programme budget, and the district allocation shares

[5] For example the degree of poverty (Ravallion, 1999; Galasso and Ravallion, 2005) or inequality (Bardhan and Mookherjee, 2000).

$\sum_{k=1}^{K} \alpha_k = 1$.

The outcome of the two stage process can then be written as a function of the size of the programme, regional targeting, local targeting rules and the characteristics of the household

$$y_{ik}^{*} = G\left(S, \alpha_k, \beta, x_{ik}, \varepsilon_{ik}\right) \tag{4.4}$$

If there is regional variation in programme intensity, α_k, then it matters where people live for the amount of benefits they will receive. The selection process of individual households by communities is represented by a vector of targeting rules, β. Targeting is also affected by the unobserved $\varepsilon_{ik} = (\eta_{ik}, v_k, \omega_{ik})$, which will be treated as random shocks to the selection process. These shocks stem from uncertainty at local level (η_{ik}), information constraints of the centre (v_k), and private information on the targeting process of programme managers (ω_{ik}). An example of the latter are preferences or priorities of local programme managers, introduced through the welfare weights, and are not observed by others.

Alternatively, equation (4.4) can be interpreted as the household's eligibility. This is a useful interpretation if the benefits that we want to investigate concern participation in a social programme. In this case the outcome of the latent targeting process (4.4) is a binary one

$$y_{ik} = 1\left[y_{ik}^{*} > 0\right] = 1\left[G\left(S, \alpha_k, \beta, x_{ik}, \varepsilon_{ik}\right) > 0\right] \tag{4.5}$$

where $1[\cdot]$ is a binary indicator function. A household is selected into the programme $(y_{ik} = 1)$ only if its eligibility, y_{ik}^{*}, exceeds a certain threshold (here normalised to zero).

Finally, the observed distribution $D(y)$ of transfers to households is a result of this targeting process, and is consequently determined by the same factors

$$D(y) = F\left(S, \alpha_k, \beta, x_{ik}, \varepsilon_{ik}\right) \tag{4.6}$$

4.3 Dynamic analysis

With the availability of more than one cross section household survey dynamic methods can be used for marginal benefit incidence analysis, by investigating how the distribution of transfers, $D(y)$, changes over time. This analysis draws on two rounds of the Susenas survey data, for 1999 and 2002. In both these years the questionnaire asks households whether they participated in the JPS scholarship and health card programme. Some restrictions arise due to the data. First, not all districts are found in both surveys because some conflict areas were left out of the 2002 survey.[6] Therefore, the analysis in this section is restricted to the districts that are represented in both years. The other problem is that information on scholarships in 2002 is only available at the household level. For each household it is known whether at least one of the children has received a JPS scholarship. To compare the two years the 1999 data is collapsed to the household level.

The size of both programmes has increased over time. The first two columns in table 4.1 show the average incidence of scholarships and health cards across per capita consumption quintiles for 1999 and 2002, at a household level. In 1999 5.2 percent of households received at least one scholarship, while in 2002 this had grown to almost 6 percent.[7] The number of households that own a health card increased from 10.9 to 14.1 percent. Average incidence is pro-poor in 1999 and 2002 for both programmes, and all quintiles benefited from the programmes expansion. The last four columns of table 4.1 show the average odds ratios and the shares of the benefits with the different quintiles. Although the poor hold the largest share in both programmes, there is considerable leakage to the non-poor. The poorest 40 percent of the population have more than 60 percent of scholarships, and almost 60 percent of health cards.

However, the change in the distribution over time differs between the two programmes. Table 4.2 shows the changes in the distributions in more detail. The table presents four commonly used measures of dynamic benefit incidence.[8]

The first column shows changes in average programme incidence over time

$$\Delta \overline{y}_{qt} = \frac{\sum_{i=1}^{N_{qt+1}} y_{iqt+1}}{N_{qt+1}} - \frac{\sum_{i=1}^{N_{qt}} y_{iqt}}{N_{qt}} \tag{4.7}$$

where y_{iqt} reflects programme participation for individual i from quintile q. Subscript t indicates time. Equation (4.7) gives the change in the probability that a household from quintile q is included in the programme: $\Pr(y_{t+1} = 1 \mid q) - \Pr(y_t = 1 \mid q)$. All quintiles benefited from the increase in number of scholarships, but the incidence amongst the poorest quintile was by far the highest. The programme expansion included 2.4 percent of the poorest households. For the second quintile this is 0.9 percent, and for the three richest quintiles less than 0.3 percent. The change in health card coverage is more equally distributed over the quintiles. Coverage amongst all quintiles increased considerably, but the pattern is far from pro-poor, ranging from 4.2 percent for the rich to 2.2 percent for

[6] The rural districts of Aceh, Maluku and Irian Jaya were not included in the 2002 survey due to local violent conflicts. These areas constituted 21 districts in the 1999 survey. East Timor (13 districts in 1999) has not been included in the Susenas after the 1999 referendum on independence.

[7] Comparing table 4.1 with the results in chapter 3 show that the observed patterns in the distribution of scholarships in 1999 are not changed by the data restrictions.

[8] See Younger (2003) for an extensive discussion of these methods.

Table 4.1: Distribution of JPS scholarships and health cards by quintile, in 1999 and 2002

	Incidence (% of population)		Average odds ratio		Share (% of total)	
	1999	2002	1999	2002	1999	2002
Scholarships						
Quintile 1	9.68	12.08	1.87	2.03	37.42	40.67
Quintile 2	6.99	7.87	1.35	1.32	27.00	26.50
Quintile 3	4.90	5.01	0.95	0.84	18.94	16.88
Quintile 4	3.05	3.32	0.59	0.56	11.79	11.18
Quintile 5	1.25	1.42	0.24	0.24	4.85	4.77
All	5.18	5.94	1.00	1.00	100.00	100.00
Health cards						
Quintile 1	19.28	22.47	1.77	1.59	35.35	31.87
Quintile 2	13.73	17.05	1.26	1.21	25.17	24.18
Quintile 3	10.87	13.08	1.00	0.93	19.94	18.55
Quintile 4	7.09	10.14	0.65	0.72	13.00	14.39
Quintile 5	3.56	7.76	0.33	0.55	6.53	11.00
All	10.91	14.10	1.00	1.00	100.00	100.00

The number of observations is 186,272 for 1999 and 212,642 for 2002.

Source: Susenas 1999 and 2002.

the third quintile. In the other quintiles about 3 percent of the household benefited from the programme increase.

The changes in average incidence have implications for the shares held by the different quintiles. The changes in the overall share of the benefits are given in the second column, that is

$$\Delta\alpha_{qt} = \frac{\sum_{i=1}^{N_{qt+1}} y_{iqt+1}}{\sum_{i=1}^{N_{t+1}} y_{it+1}} - \frac{\sum_{i=1}^{N_{qt}} y_{iqt}}{\sum_{i=1}^{N_t} y_{it}} \tag{4.8}$$

This gives change in the probability that the selected households are from a specific quintile: $\Pr(Q = q \mid y_{t+1} = 1) - \Pr(Q = q \mid y_t = 1)$. Here we see stark differences between the two programmes. The poorest quintile has increased its share of the scholarships by 3.3 percentage point, from 37.4 to 40.7 percent. The share of the other quintiles has decreased. In case of the health card programme, the two wealthiest quintiles that have increased their share, at the expense of the 3 poorest quintiles. The leakage of health cards to the non-poor has increased over time.

The change in share and average incidence do not give a complete picture on marginal incidence. They do not show how the change in benefits are distributed (Younger, 2002; van de Walle, 2004). This is given in the third column, where we observe to what extent the changes in the programmes have benefited the different quintiles. Each quintile's share in the overall changes is calculated as

$$\frac{\Delta s_{qt}}{\Delta S_t} = \frac{\sum_{i=1}^{N_{qt+1}} y_{iqt+1} - \sum_{i=1}^{N_{qt}} y_{iqt}}{\sum_{i=1}^{N_{t+1}} y_{it+1} - \sum_{i=1}^{N_t} y_{it}} \tag{4.9}$$

The poorest quintile enjoyed 55 percent of the overall increase of scholarships. The marginal shares decrease strongly for the wealthier quintiles. The rich received only 4.4 percent of the extra scholarships. The benefit of the extra health cards shows a U-shape pattern, somewhat similar to the change in average incidence. The poorest and the richest quintile received the largest share of the change, the middle quintile the least. However, only for the two richest quintiles is the share in the programme expansion larger than the initial share of the allocation. This explains the observed changes in the overall shares of benefits.

Finally, table 4.2 reports marginal odds ratios of programme expansion (following Lanjouw and Ravallion, 1999), while controlling for district specific factors

$$y_{iqkt} = c + \sum_{q=1}^{5} \theta_q d_q \overline{y}_{kt} + \gamma_q + \delta_t + \phi_k + \varepsilon_{iqkt} \tag{4.10}$$

Conditional on regional allocation, the marginal odds ratios, θ_q, indicate how the marginal benefits are distributed across quintiles. Equation (4.10) is estimated by regressing household programme participation on the programme coverage in districts, $\overline{y}_{kt}$, interacted with quintile dummy variables, d_q. This approach is similar to the marginal benefit incidence analysis in chapter 3 (page 38), except for the time dimension. Here the data for the two years have been pooled, and a year dummy variable is added to capture time effect δ_t. An advantage of using pooled household data is that both district fixed effects, ϕ_k, and quintile fixed effects, γ_q, can now be accounted for directly.[9] It is assumed that $\overline{y}_{kt}$ is not correlated with ε_{iqkt}, as regional targeting is determined solely by the centre. The marginal effects are estimated using a linear probability model and constraining the θ_q coefficients to sum to 5.

The marginal odds ratios confirm the results for the scholarship programme. Starting

[9] This application differs from previous studies, which either use regional aggregated data at different administrative levels (Lanjouw and Ravallion, 1999; Ravallion, 1999; Galasso and Ravallion 2001; Lanjouw, Pradhan, Saadah, Sayed, and Sparrow, 2002; Younger, 2003), or cross section data for individuals (Younger, 2003). The advantage of using individual over regionally aggregated data is that the statistical power of the model increases with the number of observations. Interpretation of estimates remains unchanged since the survey is representative at the district level, within the stratified survey design households are sampled from these districts, and all districts appear in both surveys.

from a pro-poor allocation in 1999, the increase of the programme over the next three years has disproportionately benefited the poor. There is no evidence of early programme capture by the non-poor, despite some non-trivial leakage. However, in case of the health card programme the marginal odds show a clear pro-poor pattern, unlike the other three measures of change.

Based on the above results, the policy implications would seem to be clear. The marginal incidence suggests that an expansion of the scholarship programme will, for the most part, benefit the poor. For the health cards this is not the case. Although the poor are the main beneficiaries, an increase in the number of health cards will benefit both the poor and the non-poor. Improving pro-poor allocation seems only possible if targeting is improved.

Table 4.2: Dynamic benefit incidence of JPS scholarships and health cards, by quintile, 1999 to 2002

	Change in incidence	Change in share	Share in change	Marginal odds ratio [1] θ_q	[s.e.]
Scholarships					
Quintile 1	2.40	3.25	54.93	1.61	[0.017]**
Quintile 2	0.88	−0.50	24.33	1.25	[0.017]**
Quintile 3	0.11	−2.06	7.85	0.97	[0.017]**
Quintile 4	0.27	−0.61	8.47	0.73	[0.018]**
Quintile 5	0.17	−0.08	4.42	0.44	[0.019]**
All	0.76	0.00	100.00		
Health cards					
Quintile 1	3.19	−3.48	22.79	1.34	[0.011]**
Quintile 2	3.32	−0.99	21.61	1.15	[0.011]**
Quintile 3	2.21	−1.39	14.92	1.04	[0.011]**
Quintile 4	3.05	1.39	18.01	0.87	[0.012]**
Quintile 5	4.20	4.47	22.67	0.60	[0.013]**
All	3.19	0.00	100.00		

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The number of observations is 186,272 for 1999 and 212,642 for 2002.

Source: Susenas 1999 and 2002.

[1] See table 4.7 (appendix) for detailed estimation results.

4.4 Decomposition and simulation.

To what extent can the distributional outcome of the programme's expansion, as observed in the previous section, be attributed to geographical targeting by the central allocation unit in Jakarta, or to local decision making? To relate this question to the outcome of the behavioural model in equation (4.6), we can view the observed change in the distribution of benefits over time, from $D_t(y)$ to $D_{t+1}(y)$, to be a result of changes in the factors that determine this distribution. Bourguignon *et al.* (2001) propose a simulation method to decompose changes in the income distribution. Their approach extends the Oaxaca-Blinder method by applying the decomposition to the full income distribution, instead of just the means of different population groups.[10] In this section I will illustrate how this methodology can be used to investigate the effectiveness of different policy instruments for targeting of public programmes.

The distribution $D_t(y)$ is determined by each household's eligibility, which in turn is determined by geographical targeting, local targeting, the household's personal characteristics and some unobserved element. Suppressing the i and k subscripts for ease of notation, indicate a household's eligibility level at time t as

$$G_t = G(S_t, \alpha_t, \beta_t; x_t, \varepsilon_t) \tag{4.11}$$

The household's eligibility level may change, which affects the probability of future participation,

$$G_{t+1} - G_t = G\left(S_{t+1}, \alpha_{t+1}, \beta_{t+1}; x_{t+1}, \varepsilon_{t+1}\right) - G(S_t, \alpha_t, \beta_t; x_t, \varepsilon_t)$$

Now imagine a counterfactual eligibility, where the size of the programme (S) is increased to the level of year $t+1$, while keeping the local targeting rules (β), the relative shares assigned to districts (α) and the population characteristics (x, ε) constant at the level of year t,

$$G_t^{\Delta\{S\}} = G\left(S_{t+1}, \alpha_t, \beta_t; x_t, \varepsilon_t\right)$$

With the allocation threshold fixed at zero, the eligibility of all households will increase, $G_t^{\Delta\{S\}} > G_t$, since more funds are available. Alternatively, we could change regional targeting, keeping all else constant,

$$G_t^{\Delta\{\alpha\}} = G\left(S_t, \alpha_{t+1}, \beta_t; x_t, \varepsilon_t\right)$$

This will increase average eligibility only in areas where $\alpha_{t+1} > \alpha_t$, since the funds allocated to those districts, $S_t\alpha_{t+1}$, increases. Average eligibility will decrease in districts where $\alpha_{t+1} < \alpha_t$.

[10] Bourguignon and Ferreira (2005) provide a detailed discussion on the generalisation of the Oaxaca-Blinder decomposition.

The Oaxaca-Blinder decomposition builds on generating an array of such counterfactual eligibility. In this way the overall change in eligibility is readily decomposed into changes in each of the determinants. These separate effects are simply introduced by adding and subtracting terms

$$\begin{aligned} G_{t+1} - G_t &= \underset{\text{(size)}}{[G_t^{\Delta\{S\}} - G_t]} + \underset{\text{(regional targeting)}}{[G_t^{\Delta\{S,\alpha\}} - G_t^{\Delta\{S\}}]} \\ &\quad + \underset{\text{(local targeting)}}{[G_t^{\Delta\{S,\alpha,\beta\}} - G_t^{\Delta\{S,\alpha\}}]} + \underset{\text{(population change)}}{[G_{t+1} - G_t^{\Delta\{S,\alpha,\beta\}}]} \end{aligned} \tag{4.12}$$

Off course, there are other paths by which the change in eligibility can be decomposed, depending on which eligibility levels are used as baseline. For example, the first effect on the right reflects the size effect. But the size effect can also be expressed as $G_t^{\Delta\{S,\alpha\}} - G_t^{\Delta\{\alpha\}}$. In the case above there are in fact 8 different representations of the size effect, using different counterfactual eligibility levels.

This highlights an important implication of the decomposition method: path dependence. It is not necessarily the case that $G_t^{\Delta\{S\}} - G_t = G_t^{\Delta\{S,\alpha\}} - G_t^{\Delta\{\alpha\}}$. There is an intuitive reason behind this. The distributional effects of expanding the programme depend on the targeting process (α_t, β_t) in the reference state. Although the availability of extra funds increases eligibility for the whole population, only those at the margin of the threshold will cross it. In other words, ranking of the population by eligibility level matters. In this particular example, the two reference states (G_t and $G_t^{\Delta\{\alpha\}}$) are subject to different geographic targeting regimes (α_t and α_{t+1}, respectively). If these regimes each yield a different ranking of the population by eligibility, then the effect of ΔS will also be different.

Note also that the population effect can be further decomposed into changes in the population characteristics, x_t, and the unobserved elements, ε_t.[11] But given the context of the paper I will restrict the analysis to separating the effect of the targeting policy

[11] One problem with decomposing the population effect is that the number of observations in the two periods is not necessarily the same. Generating the counterfactual eligibity $G_t^{\Delta\{\varepsilon\}}$ then requires to assume that the changes in unobservables ε_{ik} follow a rank preserving transformation process

$$\hat{\varepsilon}_{ikt+1} = F_{t+1}^{-1} \cdot F_t\left(\varepsilon_{ikt}\right)$$

where $F\left(.\right)$ is the cumulative distribution function. If this is assumed to be a normal distribution then the transformation process is approximated by

$$\hat{\varepsilon}_{ikt+1} = \frac{\sigma_{t+1}}{\sigma_t}\varepsilon_{ikt}$$

with σ_t is the standard deviation of ε_t. See, for example, Bourguignon *et al.* (2001) for an application of this procedure.

instruments (S, α_k, β) from the population effects.

The decomposed changes in eligibility have corresponding effects on the distribution of benefits. For example, using $D_t(y)$ as reference, four different effects can be described:

1. Size effect $D_t(y) \rightarrow D_t^{\Delta\{S\}}(y)$
2. Regional targeting effect: $D_t(y) \rightarrow D_t^{\Delta\{\alpha\}}(y)$
3. Within-district targeting effect: $D_t(y) \rightarrow D_t^{\Delta\{\beta\}}(y)$
4. Population effect: $D_t(y) \rightarrow D_t^{\Delta\{x,\varepsilon\}}(y)$

With repeated cross-section data these effects can be calculated by means of simulation. Under normality assumptions, the parameters of the targeting process $(\hat{\alpha}_k, \hat{\beta})$ are obtained for each year by probit estimation of (4.5). The unobserved component in the latent function is not readily retrieved from (4.5). However, we do need ε_{ik} since we are especially interested in those households at the margin of the eligibility threshold. Assuming that the unobserved components are void of any systematic variation, $\tilde{\varepsilon}_{ik}$ is drawn randomly from a standard normal distribution.

Eligibility and programme participation are then predicted for each household based on the estimated parameters and simulated unobservables

$$\tilde{y}_{ik} = 1\left[\tilde{y}_{ik}^* > 0\right] = 1[G(S, \hat{\alpha}_k, \hat{\beta}; x_{ik}, \tilde{\varepsilon}_{ik}) > 0] \tag{4.13}$$

This produces hypothetical distributions $\tilde{D}_t(y)$ and $\tilde{D}_{t+1}(y)$, which are similar to the observed distributions in that they are generated by the same targeting process, and differ only in the random shocks they endure. These distributions serve as base state for the decompositions. Counterfactual distributions are generated by changing the parameters in the eligibility function, and registering which households cross the threshold.

4.5 Simulation results

The probit estimates of equation (4.5) are given in table 4.3. The models include variables that are found in both the 1999 and the 2002 Susenas. These variables include local selection criteria such as characteristics of the head of household (gender, educational attainment, employment status), household welfare (per capita consumption quintiles), and household size and composition. Other variables are household living conditions (housing, water and sanitation) and a dummy variable indicating whether the household lives in a rural area. Finally, the model controls for district fixed effects, to capture the geographic targeting process.[12]

Table 4.3: JPS scholarship and health card selection, 1999 and 2002 (probit)

Variable	Scholarships 1999	Scholarships 2002	Health card 1999	Health card 2002
Female head of household	0.2626	0.1692	0.1654	0.1382
	[0.0229]**	[0.0218]**	[0.0179]**	[0.0151]**
Education head of household				
None (= reference)				
Primary	-0.0284	-0.0449	-0.0682	-0.0799
	[0.0154]†	[0.0147]**	[0.0131]**	[0.0114]**
Junior secondary	-0.1293	-0.1060	-0.1770	-0.1119
	[0.0235]**	[0.0207]**	[0.0191]**	[0.0154]**
Senior secondary	-0.1771	-0.2289	-0.2930	-0.1325
	[0.0253]**	[0.0231]**	[0.0215]**	[0.0167]**
Higher	-0.3274	-0.4181	-0.3870	-0.0849
	[0.0481]**	[0.0404]**	[0.0452]**	[0.0267]**
Head of household unemployed	0.2505	0.1723	0.0800	0.0171
	[0.0698]**	[0.0714]*	[0.0519]	[0.0475]
Per capita expenditure quintile				
Quintile 1, poorest (= reference)				
Quintile 2	-0.0013	-0.0181	-0.0959	-0.0817
	[0.0188]	[0.0176]	[0.0173]**	[0.0144]**
Quintile 3	-0.0480	-0.0728	-0.1699	-0.1535
	[0.0212]*	[0.0203]**	[0.0202]**	[0.0167]**
Quintile 4	-0.1182	-0.1453	-0.2859	-0.2436
	[0.0239]**	[0.0235]**	[0.0228]**	[0.0187]**
Quintile 5, richest	-0.2143	-0.2052	-0.4938	-0.3649
	[0.0292]**	[0.0293]**	[0.0284]**	[0.0233]**
Ln(household size)	0.6984	0.5974	0.0359	0.1029
	[0.0212]**	[0.0202]**	[0.0149]*	[0.0127]**
Household composition				
Share of males age < 6	-0.5101	-0.2696	0.3923	0.2713
	[0.0839]**	[0.0719]**	[0.0522]**	[0.0422]**
Share of females age < 6	-0.3155	-0.1993	0.3726	0.3329

Continued on next page...

[12]In a few districts the scholarships or health cards are not (yet) active. Given the district fixed-effects approach, these districts are dropped from the probit analysis since there is no variation in the outcome variable within the districts. However, they are used in the simulations, as the allocated shares to districts are changed.

... table 4.3 continued

Variable	Scholarships		Health card	
	1999	2002	1999	2002
	[0.0823]**	[0.0719]**	[0.0549]**	[0.0422]**
Share of males age 6-12	1.3461	1.8144	0.0910	0.2851
	[0.0650]**	[0.0577]**	[0.0454]*	[0.0369]**
Share of females age 6-12	1.6011	1.8476	0.1369	0.2383
	[0.0659]**	[0.0588]**	[0.0466]**	[0.0383]**
Share of males age 13-17	2.0845	1.9005	0.0656	0.0847
	[0.0662]**	[0.0607]**	[0.0486]	[0.0422]*
Share of females age 13-17	2.2600	2.0106	-0.0249	0.1682
	[0.0685]**	[0.0615]**	[0.0508]	[0.0427]**
Share of males age 18-60 (= reference)				
Share of females age 18-60	0.0562	0.0880	0.0609	0.1700
	[0.0816]	[0.0719]	[0.0398]	[0.0306]**
Share of males age > 60	-0.0929	-0.3376	0.1065	0.2078
	[0.0878]	[0.0776]**	[0.0425]*	[0.0349]**
Share of females age > 60	-0.2904	-0.2916	0.0821	0.2735
	[0.0941]**	[0.0799]**	[0.0416]*	[0.0344]**
House made out of bamboo	0.1183	0.1469	0.2573	0.2596
	[0.0207]**	[0.0208]**	[0.0180]**	[0.0171]**
Floor made out of earth	0.0621	0.0760	0.3022	0.1695
	[0.0207]**	[0.0187]**	[0.0180]**	[0.0158]**
Access to clean drinking water	-0.0745	-0.0516	-0.0380	-0.0413
	[0.0202]**	[0.0193]**	[0.0209]†	[0.0159]**
Closed sewer	-0.1186	-0.1047	-0.1958	-0.1601
	[0.0196]**	[0.0176]**	[0.0179]**	[0.0151]**
Access to electricity	-0.0597	-0.0136	-0.0476	-0.0712
	[0.0206]**	[0.0217]	[0.0225]*	[0.0192]**
Rural area	-0.0337	-0.0228	0.0011	-0.1014
	[0.0252]	[0.0213]	[0.0273]	[0.0188]**
Constant	-3.7953	-3.3437	-1.1983	-1.1950
	[0.2047]**	[0.1964]**	[0.1049]**	[0.1003]**
District fixed effects	yes	yes	yes	yes
Observations	183,657	212,226	184,458	212,642
Pseudo R-squared	0.23	0.22	0.19	0.09

Robust standard errors in brackets.

Significance levels: † : 10% $*$: 5% $**$: 1%

For both programmes, households headed by females are more eligible than male headed households, although this differences decreases over time. An increase in education attainment of the head of household decreases the probability of participation. Unemployment of the household head is a relevant criterion for the scholarship programme, but not for the health card programme. Both programmes are allocated pro-poor in terms of per capita consumption. Large households are more likely to be selected into the programmes. As expected, the probability of scholarship receipt is higher for households where the share of children at scholarships eligible age (i.e., older than 10) is relatively high. For the health card programme, households with a large share of children, women, and elderly (relative to adult men) are more likely to be selected. Household living conditions are important selection criteria for both programmes. The probability of selection in either programme increases when households live in a bamboo house, have a floor made out of earth, do not have a closed sewer, or have no access to clean drinking water or electricity.

The probit estimates are used to rank households within districts on their eligibility level, $\tilde{y}^*_{ik}$, which is the linear prediction plus the random shock $\tilde{\varepsilon}_{ik}$. The eligibility threshold is set by the number of scholarships or health cards available to a district in a specific year. For those households above the threshold $y^*_{ik} = 1$, for those below $y^*_{ik} = 0$.

The simulated baselines for the scholarship and health card programmes are shown in the first column of tables 4.4 and 4.5. The simulated shares show a similar pattern to the observed distribution. The tables further report the decomposition of the simulated changes. The top panels show the simulated change, each with 1999 as base year (i.e., $D_{1999}(y) \rightarrow D_{2002}(y)$). For example, the third column (headed by $\Delta\alpha_k$) in the top panel shows the simulated change to the 1999 distribution if it were to be subject to the 2002 geographical targeting regime $(D^{\Delta\alpha}_{1999}(y))$. The bottom panel shows results with 2002 as base (i.e., $D_{2002}(y) \rightarrow D_{1999}(y)$). The sign of the 2002 results have therefore been reversed to facilitate comparability. The results are not identical between years, emphasising the path dependency that plagues the decomposition method.[13] Nevertheless, comparing the results for both years provides some notion of precision of the estimates.

The results in table 4.4 suggest that local targeting $(\Delta\beta)$ has been a driving force behind the pro-poor increase of the scholarship programme. Keeping all other factors constant, the share of scholarships with the poorest 20 percent of the population increased by 0.7 to 1.4 percentage point because of local targeting, depending on the base year. This

[13]Note that tables 4.4 and 4.5 do not present a properly decomposed path, as described in equation (4.12). That is, the decomposed elements do not add up to the full change. Although such a decomposition can be constructed, the table only shows simulated changes relative to the baselines, $(D_{2002}(y), D_{1999}(y))$, since these effects or most relevant from a policy perspective. Tables 4.8 and 4.9 in the appendix provide examples of a correct decomposition.

Table 4.4: Simulated distribution of JPS scholarships and decomposition of changes in the distribution

		Baseline	Decomposition of changes			
			local targeting effect	regional targeting effect	size effect	population effect
			$\Delta\beta$	$\Delta\alpha_k$	ΔS	$\Delta \{x_{ik}, \varepsilon_{ik}\}$
1999	Quintile 1	35.85	1.41	−0.21	0.16	2.28
	Quintile 2	26.27	−0.56	0.27	−0.27	0.01
	Quintile 3	19.09	−0.63	0.06	0.28	−0.52
	Quintile 4	12.93	−0.27	−0.27	−0.22	−1.59
	Quintile 5	5.86	0.06	0.15	0.05	−0.19
2002	Quintile 1	39.06	0.69	0.94	−1.50	2.88
	Quintile 2	25.91	−0.18	−0.20	0.53	0.17
	Quintile 3	17.97	−0.45	−0.43	0.43	−0.82
	Quintile 4	11.27	−0.17	−0.01	0.27	−1.19
	Quintile 5	5.79	0.11	−0.30	0.27	−1.04

The number of observations is 186,272 for 1999 and 212,642 for 2002.

constitutes about a quarter of the overall increase. However, the largest effect is due to changed characteristics of the population ($\Delta \{x_{ik}, \varepsilon_{ik}\}$). The policy instruments available to the centre, on the other hand, do not show an unambiguous pattern across years. Given the 2002 local targeting policy and the relative shares allocated to districts, an increase in programme size (ΔS) has increased the share of the non-poor, at the expense of the poor. But this effect has been partly offset by improved regional targeting ($\Delta\alpha_k$). However, taking the 1999 local targeting regime as base, the effects show a less convincing pattern.

The results for the health card programme show more robust results across years (table 4.5). The pro-rich distribution of the increase in benefits is driven by local and regional targeting. Local targeting has decreased the share of the 3 poorest quintiles, and especially the poor. Changes in the allocation of health cards by local committees has been mainly to the benefit of the richest quintile, as their share increases by more than 2 percentage points. The effects of geographical targeting show a similar, albeit less profound, pattern. As geographical targeting has changed after 1999, a relatively greater weight has been assigned to districts with, on average, more wealthy households. There is also evidence of late capture by the non-poor, in the sense that expansion of the programme has benefited the fifth and fourth quintile. That is, keeping all targeting rules constant, the households at the margin of the allocation threshold are relatively wealthy.

Table 4.6 shows the concentration indices that reflect the simulated base distribution and the decomposition of changes. The concentration index (CI) is an indicator of con-

Table 4.5: Simulated distribution of JPS health cards and the decomposition of changes in the distribution

		Baseline	Decomposition of changes			
			local targeting effect	regional targeting effect	size effect	population effect
			$\Delta\beta$	$\Delta\alpha_k$	ΔS	$\Delta\left\{x_{ik}, \varepsilon_{ik}\right\}$
1999	Quintile 1	32.88	−1.21	−1.10	−2.29	1.21
	Quintile 2	26.04	−0.86	−1.03	−0.09	0.17
	Quintile 3	20.91	−0.68	−0.50	0.15	−0.84
	Quintile 4	13.73	0.59	0.75	0.98	−0.46
	Quintile 5	6.44	2.15	1.89	1.26	−0.08
2002	Quintile 1	31.01	−2.18	0.79	−1.36	1.55
	Quintile 2	24.00	−0.49	−1.28	−0.20	−0.25
	Quintile 3	19.25	−0.46	−0.94	0.33	−0.33
	Quintile 4	15.14	0.66	0.41	0.29	−0.43
	Quintile 5	10.59	2.47	1.01	0.92	−0.56

The number of observations is 186,272 for 1999 and 212,642 for 2002.

sumption related inequality in the distribution of benefits. The CI reflects the curvature of the concentration curve, which graphs the cumulative proportion of the population ranked by per capita consumption (from the poor to the rich) against the cumulative proportion of the benefits.[14] The CI is calculated as

$$CI = \frac{2}{\mu} \operatorname{cov}\left(y, r_{pc}\right) \tag{4.14}$$

where r_{pc} is a household's rank in the per capita consumption distribution, and $\mu = E\left(y_i\right)$ is mean benefits. The CI ranges from -1 (all the benefits are allocated to the poorest household) to +1 (all the benefits accrue to the richest household). An equal distribution yields a CI of zero.

The reported CI are negative for both programmes, corresponding to the pro-poor allocation. Over time the CI for the scholarship programme has become larger (more pro-poor), from -0.307 in 1999 to -0.339 in 2002. The CI for the distribution of health cards has become smaller (less pro-poor), moving from -0.267 to -0.205.

The changes correspond to the results observed in tables 4.4 and 4.5. Pro-poor targeting of marginal benefits is driven by local and regional targeting, and the population effect. The programme's expansion has had an equalising effect on the distribution of scholarships. The distribution of health cards has become more equal (i.e., less pro-poor)

[14]E.g., Wagstaff, Paci and van Doorslaer (1991), and Kakwani, Wagstaff and van Doorslaer (1997).

Table 4.6: Simulated concentration indices and decompsition of changes

		Baseline	Decomposition of changes			
			local targeting effect	regional targeting effect	size effect	population effect
			$\Delta\beta$	$\Delta\alpha_k$	ΔS	$\Delta\{x_{ik}, \varepsilon_{ik}\}$
Scholarships						
1999	$\widetilde{CI}$	-0.3073	-0.3168	-0.3078	-0.3087	-0.3312
	$\hat{\Delta}$		-0.0095	-0.0005	-0.0014	-0.0239
2002	$\widetilde{CI}$	-0.3385	-0.3346	-0.3286	-0.3513	-0.3035
	$\hat{\Delta}$		-0.0039	-0.0099	0.0128	-0.0350
Health cards						
1999	$\widetilde{CI}$	-0.2668	-0.2335	-0.2377	-0.2399	-0.2770
	$\hat{\Delta}$		0.0333	0.0291	0.0269	-0.0102
2002	$\widetilde{CI}$	-0.2045	-0.2468	-0.2119	-0.2251	-0.1885
	$\hat{\Delta}$		0.0423	0.0074	0.0206	-0.0160

The number of observations is 186,272 for 1999 and 212,642 for 2002.

because of local targeting, geographical targeting and late elite capture. This irrespective of the reference period.

Finally, the decomposition results for the targeting variables (S, α, β) are graphically illustrated in figure 4.1 for scholarships and figure 4.2 for health cards, using 2002 as base year. The advantage of the simulation based approach is that the decomposed effects can be followed over the whole distribution of per capita consumption. The figures show the change in the share of benefits (in terms of fractions) on the vertical axis. The horizontal axis ranks households from poor (0) to rich (1). Figure 4.1 shows how the largest changes have occurred at the lower end of the income distribution. It shows the offsetting effects of the change in size and the reallocation of scholarships between districts.

Figure 4.2 emphasises that the distributional changes in the health card programme due to geographical targeting are non-monotonic. Both the rich and the very poor have benefited. Both the local targeting and size effects show the gradual non-poor marginal allocation of health cards.

This simulation exercise shows that the existing measures for dynamic marginal benefit incidence can be misleading for policy advice. The traditional methods would suggest a strong pro-poor marginal distribution of scholarships, supporting the view that expansion of the scholarship programme would benefit the poor. However, the simulation results show that expanding the programme without considering the effects of local and regional targeting will do little to improve distribution of scholarships to the poor. Changing

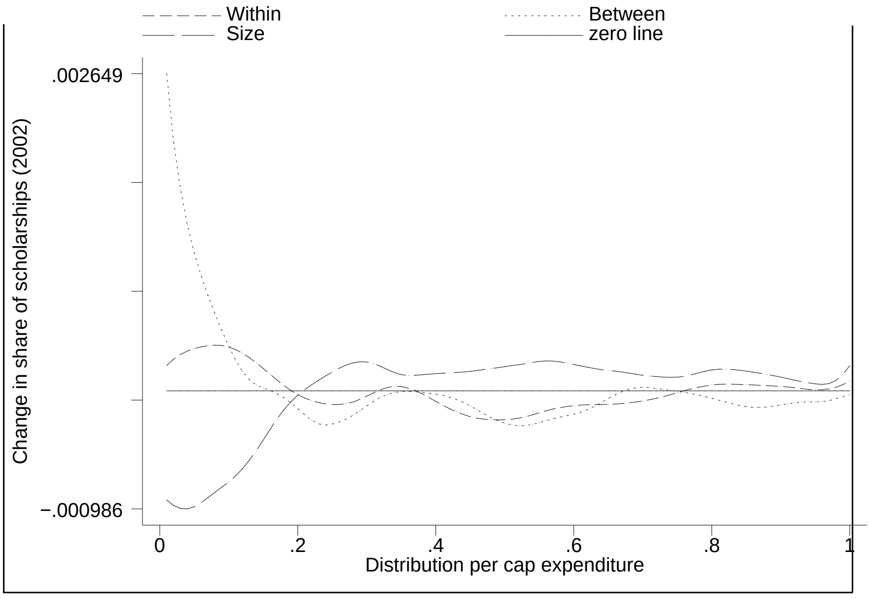

Figure 4.1: Decomposition of changes in allocation of scholarships, 2002 base (locally weighted regression, 0.3 bandwith)

the size of the programme (increase or decrease) will at most affect (benefit or hurt) the non-poor.

The results for the health card programme are consistent with the conclusions drawn from traditional methods, as the pro-rich marginal distribution is confirmed. In addition, the simulation results would suggest that while geographical targeting has not been pro-poor, improved targeting can function as instrument for reaching the poor. The redistributional effects of geographic targeting of health cards could potentially offset the pro-rich changes in local targeting. Moreover, it can improve pro-poor targeting while keeping the size of the programme constant.

4.6 Conclusion

In this chapter I applied a micro-simulation based approach for dynamic benefit incidence analysis to the Indonesian JPS scholarship and health card programmes, for the period 1999-2002. This method builds on the recent extensions of the Oaxaca-Blinder decomposition. The contribution of this method is that it provides some insight on the underlying factors driving marginal benefit incidence. Especially in a decentralised setting, the existing methods for dynamic marginal benefit incidence leave some questions unanswered.

Both the JPS health card and scholarship programmes were targeted pro-poor, while

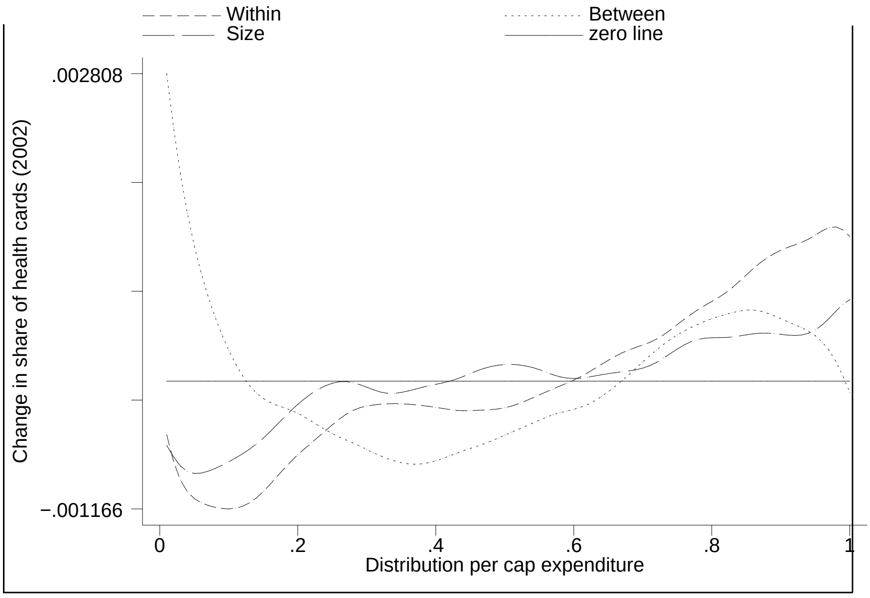

Figure 4.2: Decomposition of changes in allocation of health cards, 2002 base (locally weighted regression, 0.3 bandwith)

following a decentralised design. This design involved geographic and community based targeting. After 1999, when more accurate information on regional poverty became available, the geographic targeting rules were altered. The programmes and expanded from 1999 and 2002, but the marginal distribution of benefits show quite different patterns. The poor have been the main beneficiaries of an increase in scholarships, whereas the expansion of the health card does not show a pro-poor pattern.

The simulation based decomposition approach allows to investigate to what extent the distributional outcome of the programme's expansion is a result of changes in geographical targeting, changes in local targeting, or simply due to the expansion of the programmes.

The simulation method can provide more nuance to the observed patterns in targeting of social programmes, and facilitate interpretation of conventional marginal benefit incidence results. The exercise with the scholarship programme has shown that existing measures for dynamic marginal benefit incidence can be misleading for social policy advice. The pro-poor marginal incidence observed with the scholarship programme seem to be driven by improved local and geographical over time. Expanding the programme without simultaneously improving the targeting process will increase leakage to the non-poor. For the health card programme, the decomposition results are not conflicting with marginal incidence results. Instead, it highlights which targeting instruments would be most effective in reallocating health cards to the poor.

An important aspect of this method is path dependence, as the estimated effects are not the same for across different reference states. Often described as a potential drawback to Oaxaca-Blinder type decompositions, this path dependence can also be informative. The choice of the counterfactual baseline should be determined by the policy question mind. Observing the behaviour of the same targeting instrument in different settings can provide different, policy relevant, scenarios. Moreover, this approach allows us to compare the performance of different targeting instruments in a certain setting, or how effective these instruments are when the setting is uncertain.

4.A Supplementary tables

Table 4.7: Dynamic marginal benefit incidence analysis (linear probability estimates using pooled household data from the 1999 and 2002 Susenas)

	Scholarships		Health cards	
	Coefficient	[s.e.]	Coefficient	[s.e.]
Marginal odds ratio [1]				
Quintile 1 (θ_1)	1.614	[0.017]**	1.336	[0.011]**
Quintile 2 (θ_2)	1.249	[0.017]**	1.149	[0.011]**
Quintile 3 (θ_3)	0.966	[0.017]**	1.043	[0.011]**
Quintile 4 (θ_4)	0.732	[0.018]**	0.869	[0.012]**
Quintile 5 (θ_5)	0.439	[0.019]**	0.603	[0.013]**
Quintile dummy variables				
Quintile 1 (= reference)				
Quintile 2	-0.001	[0.002]	-0.011	[0.003]**
Quintile 3	-0.005	[0.002]*	-0.021	[0.003]**
Quintile 4	-0.010	[0.002]**	-0.026	[0.003]**
Quintile 5	-0.013	[0.002]**	-0.031	[0.003]**
Year dummy variables				
1999	0.000	[0.001]	-0.002	[0.001]*
2002 (= reference)				
Constant	0.015	[0.006]*	0.045	[0.010]**
District fixed effects	yes		yes	
Observations [2]	398,914		398,914	
Root mean square error	0.202		0.307	

[1] The θ_q coefficients are constrained to sum to 5.

[2] The number of observations is 186,272 for 1999 and 212,642 for 2002.

Table 4.8: Alternative decomposition paths for simulated changes in the distribution of JPS scholarships

	Baseline	Change	Decomposition of changes			
	D_{1999}	$D_{2002}-D_{1999}$	$D_{1999}^{\Delta\{S\}}-D_{1999}$	$D_{1999}^{\Delta\{S,\alpha\}}-D_{1999}^{\Delta\{S\}}$	$D_{1999}^{\Delta\{S,\alpha,\beta\}}-D_{1999}^{\Delta\{S,\alpha\}}$	$D_{2002}-D_{1999}^{\Delta\{S,\alpha,\beta\}}$
Quintile 1	35.85	3.21	0.16	-0.40	0.57	2.88
Quintile 2	26.27	-0.36	-0.27	-0.04	-0.22	0.17
Quintile 3	19.09	-1.12	0.28	-0.19	-0.39	-0.82
Quintile 4	12.93	-1.66	-0.22	0.19	-0.44	-1.19
Quintile 5	5.86	-0.07	0.05	0.44	0.48	-1.04
$\widetilde{CI}$	-0.3073	-0.0312	-0.0014	0.0066	-0.0014	-0.0350
	D_{2002}	$D_{2002}-D_{1999}$	$D_{2002}-D_{2002}^{\Delta\{S\}}$	$D_{2002}^{\Delta\{S\}}-D_{2002}^{\Delta\{S,\alpha\}}$	$D_{2002}^{\Delta\{S,\alpha\}}-D_{2002}^{\Delta\{S,\alpha,\beta\}}$	$D_{2002}^{\Delta\{S,\alpha,\beta\}}-D_{1999}$
Quintile 1	39.06	3.21	-1.50	1.63	0.80	2.28
Quintile 2	25.91	-0.36	0.53	-0.92	0.02	0.01
Quintile 3	17.97	-1.12	0.43	-0.44	-0.59	-0.52
Quintile 4	11.27	-1.66	0.27	0.08	-0.42	-1.59
Quintile 5	5.79	-0.07	0.27	-0.36	0.21	-0.19
$\widetilde{CI}$	-0.3385	-0.0312	0.0128	-0.0129	-0.0072	-0.0239

The number of observations is 186,272 for 1999 and 212,642 for 2002.

Table 4.9: Alternative decomposition paths for simulated changes in the distribution of JPS health cards

	Baseline	Change	Decomposition of changes			
	D_{1999}	$D_{2002} - D_{1999}$	$D_{1999}^{\Delta\{S\}} - D_{1999}$	$D_{1999}^{\Delta\{S,\alpha\}} - D_{1999}^{\Delta\{S\}}$	$D_{1999}^{\Delta\{S,\alpha,\beta\}} - D_{1999}^{\Delta\{S,\alpha\}}$	$D_{2002} - D_{1999}^{\Delta\{S,\alpha,\beta\}}$
Quintile 1	32.88	-1.87	-2.29	0.32	-1.45	1.55
Quintile 2	26.04	-2.04	-0.09	-1.23	-0.47	-0.25
Quintile 3	20.91	-1.66	0.15	-0.92	-0.56	-0.33
Quintile 4	13.73	1.41	0.98	0.41	0.45	-0.43
Quintile 5	6.44	4.15	1.26	1.41	2.04	-0.56
$\widetilde{CI}$	-0.2668	0.0623	0.0269	0.0194	0.0320	-0.0160
	D_{2002}	$D_{2002} - D_{1999}$	$D_{2002} - D_{2002}^{\Delta\{S\}}$	$D_{2002}^{\Delta\{S\}} - D_{2002}^{\Delta\{S,\alpha\}}$	$D_{2002}^{\Delta\{S,\alpha\}} - D_{2002}^{\Delta\{S,\alpha,\beta\}}$	$D_{2002}^{\Delta\{S,\alpha,\beta\}} - D_{1999}$
Quintile 1	31.01	-1.87	-1.36	0.38	-2.10	1.21
Quintile 2	24.00	-2.04	-0.20	-1.44	-0.57	0.17
Quintile 3	19.25	-1.66	0.33	-0.94	-0.21	-0.84
Quintile 4	15.14	1.41	0.29	0.71	0.87	-0.46
Quintile 5	10.59	4.15	0.92	1.30	2.01	-0.08
$\widetilde{CI}$	-0.2045	0.0623	0.0206	0.0146	0.0373	-0.0102

The number of observations is 186,272 for 1999 and 212,642 for 2002.

Chapter 5

Protecting Education for the Poor in Times of Crisis: An Evaluation of a Scholarship Programme in Indonesia

5.1 Introduction

Protecting access to education for the poor in times of economic crisis is a primary policy concern in low-income countries, since investment in education is generally considered to be a key factor in reducing poverty.[1] These investments are compromised when households are faced with unexpected transitory income shocks, such as resulting from the economic crisis. Under typically incomplete financial markets, the investment decisions of households are bound by credit and resource constraints (e.g. Jacoby and Skoufias, 1997). Households' consumption smoothing strategies may then involve reducing investments in education or relying on child labour to smooth consumption.[2]

[1]Many empirical studies have stressed the importance of investment in education, in particular basic education, for future earnings. For an overview see, for example, Schultz (1988), Psacharopoulos (1994) and Jimenez (1995). Although the reliability of methods for estimating returns on future earnings has often been questioned, there are some studies for Indonesia where the typical endogeneity problems have been addressed. Duflo (2001) identifies economic returns to education by exploiting exogenous regional and inter-temporal variation in a school construction program in the 1970s. She finds rates of return of basic education that range between 6.8 to 10.6 percent. Using 1986 survey data and controlling for unobserved heterogeneity at household an community level, Behrman and Deolalikar (1995) estimate returns to an additional year of primary education of around 5 percent on earnings. They find returns to secondary education of 5.3 to 5.9 for boys and 7.1 to 10.3 for girls. Similar results are reported in Behrman and Dealolikar (1991) and (1993).

[2]There is some empirical work that explicitly studies the role of human capital investment in household consumption smoothing strategies. In the case of Indonesia Cameron and Worswick (2001) find evidence of consumption smoothing through reduced education expenditures (especially for girls) amongst rural households as a reaction to crop loss. Fitzsimons (2003) finds for small Indonesian villages that enrolment

Targeted scholarship programmes can be cost-effective instruments for protecting investments in education for the poor. There are several studies that provide evidence that price subsidy programmes are indeed effective in increasing school participation and reducing child labour.[3] This chapter evaluates the effects of such a demand side intervention within the context of an economic crisis. In particular, the chapter evaluates the extent to which the Indonesian Social Safety Net intervention - *Jaringan Pengaman Social* (JPS) - has been able to protect access to education for the poor during the first year of the programme. The chapter looks at the impact of the scholarships on both enrolment status of children and the actual activities of students, i.e., school attendance and work.

The scholarships can affect school attendance or work activities, even without having an observable effect on enrolment. School attendance and child work are not mutually exclusive or perfect substitutes.[4] Suryahadi, Priyambada and Sumarto (2005), find that in Indonesia schooling and part time work often go together. Although the declining trend in child labour, observed during the past 3 decades, has come to a halt with the onset of the crisis, they find that working does not exclude children from attending school. They even find evidence that students from severely poor families seek employment to finance their own education. There is a growing number of empirical studies that investigate the simultaneous nature of labour and schooling decisions[5]. This chapter adds to this work, by estimating the impact of the JPS scholarships on the joint decision of school attendance and child labour.

To deal with the non-random allocation of scholarships, the identification strategy exploits the decentralised targeting design of the programme. In principle, the scholarships were targeted pro-poor, at both the individual and the district level. However, due to the heterogeneous nature of the crisis across districts, only incomplete information on regional poverty was available to policy makers. For the first year of the programme, geographic allocation was therefore based on outdated pre-crisis poverty estimates from

is mainly affected by aggregate instead of idiosyncratic risk. For empirical studies on the effects of income volatility on schooling and child labour, in relation to credit markets, see Flug, Spilimbergo and Wachtenheim (1998), Dehejia and Gatti (2002), and Beegle, Dehejia and Gatti (2003).

[3]The conditional cash transfer (CCT) component of the Mexican PROGRESA programme increased school enrolment and attendance, and reduced child work activities (Skoufias and Parker, 2001; Schultz, 2004; Behrman *et al.* ,2005; and Parker *et al.* 2005). Similar results have been found with other CCT programmes in Latin America (Rawlings and Rubio, 2003; Maluccio and Flores, 2004). Ravallion and Wodon (2000) find increased schooling and decreased child work as a results from a food-for-education programme in Bangladesh.

[4]With regard to school subsidy programmes, Ravallion and Wodon (2000), Skoufias and Parker (2001) and Schultz (2004) all find that the positive effects on schooling are only partly explained by reduced labour activities.

[5]See, amongst others, Canagarajah and Coulombe (1997), Nielsen (1998), Ridao-Cano (2001), Maitra and Ray (2002), and Rosati and Rossi (2003).

1996. The lack of reliable data at the initial phase of allocation caused some degree of unintended mis-targeting to districts. This exogenous variation in the targeting process is used to identify the treatment effects. Instrumental variables are constructed from the initial selection rule and ex-post information on the poverty profile. The availability of pre-intervention data makes it possible to assess the validity of regional mis-targeting as instrument.

The programme appears to have been successful in returning enrolment to pre-crisis levels, especially for children of primary school age from poor rural households. The scholarships also enticed households to reallocate a child's time from work to school. However, in contrast to other studies, labour activities of enrolled students show to be more sensitive to scholarships than school attendance. The results emphasise the relationship between transitory income shocks and households' investment in human capital. The scholarships were most effective for children whose education was especially vulnerable to consumption smoothing during the crisis.

The chapter is structured as follows. The next section describes the data. Section 5.3 gives a short account of the education outcomes during the crisis.[6] Section 5.4 deals with identification and estimation of the programme's impact, and section 5.5 concludes.

5.2 The data

As in the previous chapters, the main source of data for this analysis is Indonesia's annually conducted national socioeconomic survey (*Susenas*). The Susenas collects information on education, socioeconomic background of individuals and households, and detailed information on household expenditures. Besides school enrolment the survey also collects information on the activities of children in the previous week. Children aged 10 and older are asked about school attendance, labour, house work, and other activities. The special JPS module of 1999 provides the information on programme participation for each child. Since the survey is fielded in February the JPS module only covers the first 6 months of the programme. The 1999 survey includes 205,747 households and 864,580 individuals.

The Susenas is representative at the district level (*kabupaten* and *kota*). The 1998 and 1999 cross section data can be used to construct a pseudo-panel of two waves for 294 districts.[7] The 1998 survey was fielded in February 1998, about 6 months prior to the JPS programme, and includes 207,645 households and 880,040 individuals. It collects the same information as the 1999 survey, except for the JPS data.

[6] For a more detailed overview of education during the crisis (and references to other studies) see chapter 2.

[7] The districts of East Timor are not included in the analysis due to incomplete data.

Another source of data is the 1996 *Podes* village census, which will provide information on the availability of schools in each village (*desa*) and township (*kelurahan*) in Indonesia. The 1996 Podes includes 66,486 villages and is merged with the Susenas data at village level. Finally, I will use administrative data for the district selection criteria and budget allocation for the scholarship programme, documented in the 1998 *Programme Implementation Plan* (Ministry of Education, 1998).

5.3 The economic crisis and investments in education

In chapter 2 it was shown that there is some evidence that expenses on education were reduced to smooth consumption during the crisis. The main conclusions based on the observed trends in the Susenas data and findings from other studies is that investments in education did suffer from the crisis, especially for the rural poor, but that households seem to have protected education of the older children at the expense of their younger siblings. The positive trend in primary and junior secondary enrolment was halted in 1998, but recovered again in 1999.

Table 5.1: School attendance in previous week amongst enrolled children (percentage), by enrolment level and age group in 1999

	JPS	Non-JPS	Work	No work	All
Enrolment					
Primary	97.6	98.2	91.5	98.4	98.1
	[0.33]	[0.11]	[0.80]	[0.11]	[0.11]
Junior Secondary	97.6	98.2	92.2	98.6	98.1
	[0.36]	[0.11]	[0.66]	[0.10]	[0.11]
Senior Secondary	97.8	98.5	94.7	98.8	98.5
	[0.80]	[0.13]	[0.71]	[0.12]	[0.13]
Age group					
10 to 12	97.8	98.4	94.1	98.5	98.4
	[0.34]	[0.11]	[0.83]	[0.10]	[0.10]
13 to 15	97.5	98.2	92.2	98.6	98.2
	[0.34]	[0.11]	[0.67]	[0.10]	[0.11]
16 to 18	97.4	97.9	92.0	98.5	97.9
	[0.61]	[0.13]	[0.71]	[0.11]	[0.13]
10 to 18	97.6	98.2	92.6	98.6	98.2
	[0.25]	[0.09]	[0.49]	[0.08]	[0.09]
N	8,503	111,519	8,505	111,517	120,022

Standard errors in square brackets are adjusted for clustering in survey design

To a large extent the increase in enrolment in 1999 has been attributed to the JPS programme, mainly on the grounds that the programme has been fairly successful in targeting the poor (Jones and Hagul, 2001; Dhanani and Islam, 2002). However, a comprehensive evaluation of the impact of the programme has not been carried out yet. Cameron (2002) does find a positive effect of the programme, using a dataset concerning 100 predominantly poor villages. She finds significant effects only for junior secondary education.

Being enrolled does not automatically mean that students actually go to school. Enrolment takes place in August and typically requires sunk costs such as a one time enrolment fee and costs for school uniforms and books. Variable schooling costs include transportation costs and monthly tuition fees.[8] For consumption smoothing reasons, it could be that enrolled children may not attend school because of these variable costs of schooling. Alternatively, they may decide to work, which could reduce time spent at school.[9]

Table 5.2: Labour activities in previous week (percentage), by enrolment level and age group in 1999

	Enrolled			Not enrolled	All
	JPS	Non-JPS	All		
Enrolment					
Primary	7.9	3.6	3.9		
	[0.59]	[0.13]	[0.13]		
Junior Secondary	12.1	7.3	7.7		
	[0.75]	[0.22]	[0.22]		
Senior Secondary	13.6	7.2	7.5		
	[1.56]	[0.26]	[0.26]		
Age group					
10 to 12	6.5	2.8	3.0	20.4	3.7
	[0.58]	[0.11]	[0.12]	[1.08]	[0.13]
13 to 15	11.8	6.6	7.1	38.5	13.7
	[0.72]	[0.19]	[0.20]	[0.68]	[0.24]
16 to 18	14.8	8.8	9.0	52.2	30.2
	[1.27]	[0.27]	[0.27]	[0.49]	[0.35]
10 to 18	10.2	5.5	5.8	46.6	15.9
	[0.53]	[0.13]	[0.14]	[0.43]	[0.19]
N	8,503	111,519	120,022	40,018	160,040

Standard errors in square brackets are adjusted for clustering in survey design

[8] Annual sunk costs for enrolment fees, school uniforms and books constitute 25 percent of average total education expenditures per child in the 1997/1998 school year (Pradhan and Sparrow, 2000). About 11 percent of total expenditures are due to daily transportation, while monthly tuition and BP3 (i.e. parent-teacher association) fees take account of 29 percent.

[9] Qualitative research by Jones *et al.* (2003) finds anecdotal evidence to support this hypothesis.

Table 5.1 looks at school attendance in the past week for enrolled students, in 1999.[10] School attendance is fairly high for all enrolment levels and age groups, varying around 98 percent. However, programme participants have a slightly lower attendance rate than non-participants, on average just over half a percentage point. Columns 5 and 6 show that working doesn't prevent children from attending school. However, enrolled children that work are more often absent from school. Working is here defined as activities that contribute to household income, for at least one hour in the last week. This may include wage labour, but also non wage labour such as own farm activities.

Table 5.2 depicts labour activities for scholarship recipients, enrolled children without a scholarship and non-enrolled children. Enrolled children without a scholarship are less likely to work than those with a scholarship. Scholarship recipients work, on average, twice as much as non recipients (10.2 and 5.5 percent, respectively). Labour activity is highest for non-enrolled children. 46.6 percent of non-enrolled children aged 10 to 18 work at least one hour a week.

5.4 The impact of the scholarship programme

5.4.1 Regional mis-targeting

The foremost and obvious problem for measuring the effect of the programme is that the scholarships were not assigned randomly, but have been targeted to students from poor households instead. Poor households are expected to be more likely to take their children out of school or have them participate in labour activities, in response to the effects of the crisis. In the absence of the scholarship programme, enrolment and school attendance would be expected to be lower for scholarship recipients, given that they come from, on average, poorer households than non-recipients. For the same reason the probability of working is expected to be higher. Consequently, children without a scholarship do not form a suitable control group for children that are selected for the programme.

A variety of approaches can be used to deal with non-random allocation of scholarships (e.g., Heckman, LaLonde and Smith, 1999). A frequently applied method is to use instrumental variables, which relies on finding some source of exogenous variation that affects the probability of receiving a scholarship, but is independent of the potential outcomes. The former assumption can easily be verified, but the latter is difficult to test, and often relies on economic reasoning.

[10]This refers to the full week prior to enumeration, which took place in February, one month into the second semester of the 1999/2000 school year.

With regard to the JPS programme, the endogeneity has its source with both geographic and individual targeting. Ravallion and Wodon (2000) exploit the decentralised nature of the allocation process to find a valid instrument. They argue that partial decentralisation creates *geographic separability*, where the probability of selection into the programme is conditional on geographic allocation, and independent between areas.[11] Under the assumption of geographic separability, exogenous variation in geographic targeting can be used to identify the effect of the programme. It may be easier to find an instrument at district level than at individual level since the dimensions of the targeting process (and possible unobservables) are smaller.

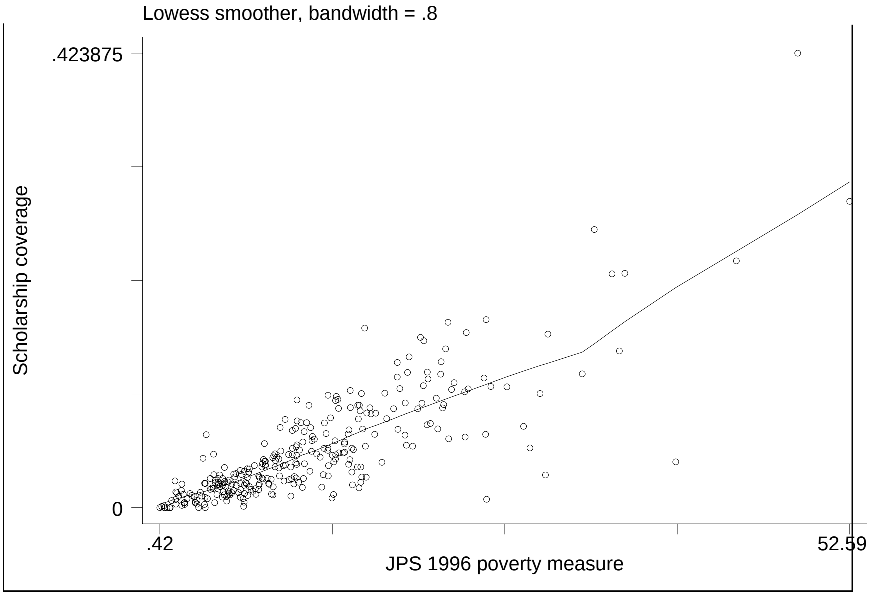

Figure 5.1: Correlation between $JPS96_j$ and scholarship coverage ($\overline{T}_j$).

Targeting of scholarships to districts was based on just two criteria: the 1996 poverty estimate ($JPS96$) and the number of enrolled students in the district. A district level regression shows that the $JPS96$ measure and the 1998 enrolment rates explain 69 percent of the variation in the fraction of scholarships recipients across districts.[12] There is a strong positive correlation between the $JPS96$ measure and scholarship coverage, but it doesn't fully explain actual allocation (see figure 5.1). There can be several reasons for actual allocation in districts to deviate from the targeting rule. First, the timing of the programme and the Susenas may introduce unobserved variables that affect allocation. Remember that at the time of the survey, February 1999, not all the targets had been met yet, and this delay in implementation varied across districts. Moreover, there may be

[11] This assumes no inter-district migration due to the programme.
[12] Results not shown here.

differences in the effectiveness and efficiency of the allocation systems between districts.

Chapter 3 has shown that given the heterogeneous nature of the crisis and the lack of up to date information available to programme management, it is likely that the first stage targeting rule misjudged the degree of poverty in the districts. Mis-targeting of districts can provide the exogenous variation needed to identify the effect of the scholarship programme. To put the argument more formally, decompose the $JPS96$ measure into two components

$$JPS96_j = \psi' V_j + z_j \tag{5.1}$$

where V_j reflects the actual poverty profile in 1998 and the impact of the crisis for district j. The *mis-targeting* term, z_j, is a non-systematic judgement error in the targeting process. It reflects the inability to capture the extent of poverty during the crisis due to the lack of information on the actual situation in 1998.

With the belated availability of information on the regional poverty profile in 1998, z_j can be estimated by taking the residual of the regression $E[JPS96_j \mid V_j]$. If conditioning on V_j indeed purges $JPS96_j$ of all systematic variation then $\hat{z}_j$ would be a suitable instrument. For example, if $JPS96_j$ overestimates the actual degree of poverty in 1998 (V_j) for district j, then $z_j > 0$. Given sufficient available information on poverty profile V_j, the estimated overestimation $\hat{z}_j$ should be independent from the enrolment rate, and the extent of school attendance and child labour in that district.

With a strategy like this there remains the danger that V_j is not fully observable, in which case the omitted variables will cause $\hat{z}_j$ to contain some poverty related variation. One way to evaluate the credibility of the identification strategy is to test whether $\hat{z}_j$ is correlated with the pre-intervention outcomes (Pradhan, Rawlings and Ridder, 1998), using data from Susenas 1998. The identifying assumption for estimating the impact of the programme is that if the exclusion restriction is valid for 1998, it also is for 1999. This seems a reasonable assumption since $JPS96$ is based on historic poverty estimates, and the impact of the crisis across districts seems not to be correlated with pre-crisis poverty (e.g. chapter 3).

Table 5.3 shows the results from district level regressions of 1998 enrolment, school attendance and child labour rates for children age 10 to 18, on $\hat{z}_j$ and $JPS96_j$, respectively.[13] The regional poverty profile V_j includes the 1998 headcount (P_0) and the poverty gap (P_1) for each district.[14] An alternative poverty headcount estimate for 1996 ($BPS96$),

[13]Figures 5.2 to 5.7 in the appendix 5.C show the results graphically with partial-regression leverage plots.

[14]P_0 and P_1 are estimated based on per capita household expenditure. The expenditure data comes from Susenas. The povertylines are set such that the average head count for Indonesia is 24.1% in February 1998 and 27.1% in February 1999 (Suryahadi, Sumarto and Pritchett, 2003).

released by the Indonesian Bureau of Statistics in 2000, is included to capture the impact of the crisis.[15] The results suggest that given the specification of V_j, the exclusion restriction is justified. Enrolment and labour are strongly correlated with $JPS96_j$, while school attendance is not (top panel). Districts that the JPS programme regarded as relatively poor, experience lower enrolment and higher incidence of child labour. However, the mis-targeting residual $\hat{z}_j$ shows no correlation with the outcome variables, as the coefficients are small and statistically not significant (bottom panel). Note that for enrolment and attendance it suffices to just condition on P_0 and P_1 to remove the systematic variation in $\hat{z}_j$.

Table 5.3: Relation between 1998 pre-intervention outcomes and geographic (mis-) targeting (OLS estimates)

	Enrolment rate	Attendance rate	Child labour rate
$JPS96_j$	-0.342	-0.017	0.188
	[0.065]**	[0.015]	[0.040]**
Constant	0.786	0.988	0.039
	[0.009]**	[0.002]**	[0.006]**
R-squared	0.0870	0.0043	0.0707
$\hat{z}_j$	-0.083	-0.004	0.046
	[0.087]	[0.019]	[0.062]
Constant	0.746	0.986	0.061
	[0.006]**	[0.001]**	[0.003]**
R-squared	0.0031	0.0001	0.0019

Standard errors in square brackets.

Significance levels: † : 10% $*$: 5% $**$: 1%

Note: Outcome variables are district means from Susenas 1998. N = 294.

5.4.2 The effect on enrolment

Estimation

The overall effect of the JPS scholarships on enrolment is estimated at the district level, by explaining regional variation in the enrolment rate by the variation in the size of the programme across districts.[16] For each district j the enrolment rate in year t is modelled

[15] The estimates and methodology are reported in BPS (2000).

[16] Pitt, Rozensweig and Gibbons (1995) follow a similar approach, applying difference in difference estimation to regionally aggregated data in Indonesia in order to investigate the determinants of school attendance and child morbidity. Analysis at the individual level is problematic since we do not observe children that receive a scholarship, but are no longer enrolled. Therefore, there is no variation in treatment assignment T_i for non-enrolled students. Ideally, I would like to have information on students histories of receiving scholarships, but, unfortunately, the Susenas does not contain these data. But even if these

as a linear function of the intensity of the scholarship programme

$$s_{jt} = \alpha_j + (\tau + \eta_j)\,\overline{T}_{jt} + \phi' W_{jt} + \theta_0 d_t + \sum_{r=2}^{5} \theta_r d_r d_t + \varepsilon_{jt} \tag{5.2}$$

where

$$\overline{T}_{jt} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} T_{ijt}$$

T_{ijt} denotes selection into the programme, N_j is the total number of children (for the specific group) in district j and s_j is the enrolment rate for a specific age group or enrolment level in district j (as reported in table 2.1). $\overline{T}_{jt}$ is the fraction of children that received a scholarship in that group. Thus, both s_{jt} and $\overline{T}_{jt}$ refer to the same potential JPS target group of school age children. The average effect of the programme is defined as $E[\tau_j] = \tau$, where τ_j is the idiosyncratic effect for each district. Effect heterogeneity is then reflected by $\eta_j = \tau_j - \tau$. This is the average deviation from τ in a specific district, with $E[\eta_j] = 0$. Time is indicated by subscript t, which is either 1998 (pre-intervention) or 1999 (post-intervention). In 1998 no JPS scholarships have been allocated, thus $\overline{T}_{j1998} = 0$ for all j. W_j is a set of control variables that capture labour market, welfare and demographic characteristics in the districts. The time dummy variable d_t takes value 1 if $t = 1999$ and 0 if $t = 1998$. Some flexibility is given to capturing the time trend by interacting time variable d_t with region specific fixed effects, d_r.[17] α_j is a time invariant fixed effect. This accounts for all endogeneity that has its source with non-random placement based on district specific time invariant variables. The bias due to targeting of poorer districts (using the historic $JPS96$ measure) is thereby removed, as well as any bias due to time invariant unobservables.

Taking first differences of (5.2) yields

$$\Delta s_j = (\tau + \eta_j)\,\overline{T}_j + \phi' \Delta W_j + \theta_0 + \sum_{r=2}^{5} \theta_r d_r + \Delta\varepsilon_j \tag{5.3}$$

OLS will give unbiased estimates for (5.3) under two assumptions. First, the time trend is assumed to be constant within the five regions. This assumption is violated if there is any geographical variation in the change of the average economic conditions that is not captured by the time dummies or ΔW_j. For example, the crisis may have systematically

had been available, it would be likely to find very few scholarship recipients to drop out of school so early into the programme, providing very little variation in the outcome variable for recipients.

[17] The 5 regions are (i) Java and Bali, (ii) Sumatra, (iii) Sulawesi, (iv) Kalimantan and (v) Other Islands. Java and Bali serve as the reference group.

different effects for rich districts than for less wealthy districts, within the regions. The second assumption is that there are no time varying unobservables that are in any way correlated with the allocation process. If either of these two assumptions does not hold then $\overline{T}_j$ will be correlated with $\Delta\varepsilon_j$. In this case the bias can be removed by IV estimation using $\hat{z}_j$ as instrument.[18]

Interpretation of the estimates depends on assumptions regarding the expected effect heterogeneity. Unobserved effect heterogeneity requires strong assumptions if IV estimates are to be interpreted as average treatment effects (Heckman, 1997). For example, it would be sufficient to assume that regional allocation is independent of the unobserved effect heterogeneity, $E[\eta_j \mid \overline{T}_j] = 0$.[19] In this case both IV and OLS identify the average treatment effect, $E[\hat{\tau}_{ATE}] = \tau$. This seems to be a reasonable assumption, since geographic targeting was not based on the expected average gains within districts. However, actual allocation $\overline{T}_j$ depends on 1996 poverty estimates and the speed of programme implementation per district. If these are correlated with the heterogeneous effect of the programme then $E[\eta_j \mid \overline{T}_j] \neq 0$, even if this was not known a priori to programme managers. In this case OLS will retrieve the average treatment effect on the treated, $E[\hat{\tau}_{ATT}] = \tau + E[\eta_j \mid \overline{T}_j]$. This captures the fraction of the actual programme participants that would have dropped out of school if they had not received a scholarship. IV, on the other hand, will identify the *local* average treatment effect (LATE), $E[\hat{\tau}_{LATE}] = \tau + E[\eta_j \mid \overline{T}_j(\hat{z}'_j) > \overline{T}_j(\hat{z}''_j)]$, proposed by Imbens and Angrist (1994).[20] This is the average treatment effect for those districts where allocation $\overline{T}_j$ is affected by $\hat{z}_j$. In this respect, the mis-targeting term is an appealing instrumental variable. Under the assumption that the probability of receiving a scholarship is conditional on geographic allocation, the LATE can be interpreted as the effect of marginal changes in geographic targeting policy.

[18] An additional source of bias is measurement error in the Susenas data, since the JPS module records scholarship information only for enrolled students. The extent of this bias depends on the number of scholarship recipients dropping out of school in the first months of the programme. While this bias is not likely to be large (footnote 16), it cannot be ignored when interpreting the OLS estimates.

[19] Note that $E[\Delta s_j] = \tau\overline{T}_j + \phi'\Delta W_j + \theta_0 + \sum \theta_r d_r + e_j$, where the unobserved $e_j = E[\eta_j T_j] + E[\Delta\varepsilon_j]$. Since z_j is correlated with $\overline{T}_j$ by assumption, z_j is correlated with e_j if $E[\eta_j \mid \overline{T}_j] \neq 0$, even if the instrument is not correlated with the outcome variable, $E[\Delta\varepsilon_j \mid \overline{T}_j, \Delta W_j, d_r] = E[\Delta\varepsilon_j \mid \Delta W_j, d_r] = 0$. See Angrist (2004) for a discussion on assumptions (weaker than effect homogeneity) that allow IV to identify average treatment effects.

[20] LATE imposes a monotonicity assumption. Let $\overline{T}_j(\hat{z}'_j)$ be $\overline{T}_j$ given $\hat{z}_j = \hat{z}'_j$. Monotonicity requires that for $\hat{z}'_j$ and $\hat{z}''_j$, in the support of $\hat{z}_j$, it must hold that either $\overline{T}(\hat{z}'_j) \leq \overline{T}(\hat{z}''_j)$ or $\overline{T}(\hat{z}'_j) \geq \overline{T}(\hat{z}''_j)$ for all j. Intuitively, this would imply that when the degree of poverty-overestimation ($\hat{z}_j$) in a district increases this will never decrease the probability of receiving a scholarship for any child in that district.

The overall effect of the programme on the enrolment rate is given by a population weighted average of the effects for the districts

$$E[s^1_{1999}] - E[s^0_{1999}] = \hat{\tau} \sum_{j=1}^{J} \frac{N_j}{N} \frac{1}{N_j} \sum_{i=1}^{N_j} T_{ij} = \hat{\tau}\overline{T} \tag{5.4}$$

where $\overline{T}$ is the fraction of the relevant (subset of the) population that has received a scholarship, and J the number of districts. s^1_{1999} is the actual enrolment rate that we observe in 1999 with the programme in place. The counterfactual s^0_{1999} is the enrolment rate that would have been if the programme was not implemented.

Results

Table 5.4 shows the OLS and IV impact estimates for equation (5.3) and the effect on the enrolment rate, $\hat{\tau}\overline{T}$ (equation (5.4)), for all children aged 10 to 18, and for the three age groups.[21] The estimated effects for net enrolment are given in table 5.5. The tables also report $\overline{T}$. The welfare variables, W_j, include the share of rural population, average age, average household size, and poverty indictors P_0 and P_1 in the district. The coefficients for the covariates are omitted from the table for convenience. The number of observations is 294. The first stage coefficient for the instrument (denoted by $\hat{\delta}_z$) is positive and strongly significant in all regressions. Over-estimation of poverty increases the intensity of the programme in a district.

There is a significant effect of the programme on enrolment. The IV estimates of the programme are larger and more precise than the OLS estimates. This suggest some correlation between $\overline{T}_j$ and $\Delta\varepsilon_j$. The most likely explanation would seem to be a non-constant time trend due to regional variation in the crisis effect.[22]

According to the IV estimates, 13 percent of programme participants would have dropped out of school if they had not received a scholarship. The effect for children aged 10 to 12 is 10 percent. For children between ages 13 and 15 it is slightly higher, at 12 percent, but this estimate is not precise. For the age group 16-18 there is no significant effect on enrolment.

[21] Weights are applied to take account of the underlying number of observations used for calculating district means.

[22] It could also be that IV retrieves a LATE that differs strongly from ATT or ATE. For example, if some districts experience delays in programme implementation. In 7 out of 294 districts used in estimation, no children reported to have received a scholarship yet ($\overline{T}_j = 0$). Using the terminology of Angrist, Imbens and Rubin (1996), these districts can be thought of as *never takers.* Neither the LATE nor ATT reflect the effects for these districts. However, the estimates are not sensitive to including a dummy variable that indicates the 7 never takers (see table 5.13 in appendix 5.B). The dummy coefficients ($\hat{\theta}_{no-treat}$) are small and not significant in all regressions.

Turning to net enrolment, there is only an effect for primary school level (18 percent increase). So the bulk of the effect picked up for 13 to 15 year olds is due to students who are still in primary school (either because of delayed enrolment or grade repetition). This is an important result. These students are likely to be in the higher grades of primary school. In absence of the programme they would have dropped out of school just prior to finishing primary education.

Table 5.4: Effect of the JPS scholarships on enrolment (equations (5.3) and (5.4))

Age group	$\hat{\tau}$	[s.e.]	$\hat{\tau}\overline{T}$	$\overline{T}$	$\hat{\delta}_z$	[s.e.]
OLS						
10 to 12	0.076	[0.026]**	0.0044	0.058		
13 to 15	0.037	[0.051]	0.0025	0.068		
16 to 18	0.046	[0.138]	0.0011	0.024		
10 to 18	0.053	[0.048]	0.0027	0.050		
IV						
10 to 12	0.100	[0.035]**	0.0058	0.058	0.772	[0.043]**
13 to 15	0.117	[0.074]	0.0079	0.068	0.801	[0.050]**
16 to 18	−0.002	[0.236]	-0.0000	0.024	0.305	[0.025]**
10 to 18	0.126	[0.065]†	0.0063	0.050	0.642	[0.035]**

Significance levels: † : 10% $*$: 5% $**$: 1%
Number of observations is 294.

Table 5.5: Effect of the JPS scholarships on net enrolment (equations (5.3) and (5.4))

School level	$\hat{\tau}$	[s.e.]	$\hat{\tau}\overline{T}$	$\overline{T}$	$\hat{\delta}_z$	[s.e.]
OLS						
Primary	0.150	[0.049]**	0.0088	0.058		
Junior Secondary	-0.057	[0.045]	-0.0039	0.068		
Senior Secondary	-0.043	[0.057]	-0.0010	0.024		
IV						
Primary	0.178	[0.067]**	0.0104	0.058	0.819	[0.045]**
Junior Secondary	0.022	[0.069]	0.0015	0.068	1.046	[0.072]**
Senior Secondary	0.021	[0.111]	0.0005	0.024	0.605	[0.059]**

Significance levels: † : 10% $*$: 5% $**$: 1%
Number of observations is 294.

The effects for different groups in the population are given in table 5.6. The table shows the estimates by per capita consumption group, gender and rural/urban area. Three per capita consumption groups are defined: the 1st-25th percentile (i.e., the poorest quarter of the population), 25th-50th percentile and the 50th-100th percentile. The poorest quartile

Table 5.6: Effect of the JPS scholarships on enrolment, by per capita consumption, gender and urban/rural (IV estimates for equation (5.3))

Sub group	OLS		IV		
	$\hat{\tau}$	[s.e.]	$\hat{\tau}$	[s.e.]	N
10 to 12					
1-25 percentile	0.063	[0.042]	0.122	[0.059]*	293
25-50 percentile	0.081	[0.042]†	0.043	[0.066]	294
50-100 percentile	−0.015	[0.039]	−0.021	[0.064]	294
male	0.087	[0.031]**	0.098	[0.045]*	294
female	0.068	[0.033]*	0.109	[0.046]*	294
urban	0.064	[0.032]*	0.055	[0.060]	287
rural	0.046	[0.031]	0.105	[0.042]*	277
13 to 15					
1-25 percentile	0.208	[0.073]**	0.201	[0.108]†	293
25-50 percentile	−0.077	[0.083]	−0.023	[0.129]	294
50-100 percentile	−0.009	[0.080]	0.074	[0.143]	294
male	0.111	[0.063]†	0.163	[0.096]†	294
female	0.042	[0.059]	0.067	[0.090]	294
urban	0.055	[0.064]	0.084	[0.111]	287
rural	0.035	[0.055]	0.134	[0.081]†	277
16 to 18					
1-25 percentile	0.158	[0.186]	−0.076	[0.396]	291
25-50 percentile	0.007	[0.208]	−0.291	[0.443]	294
50-100 percentile	0.023	[0.179]	−0.141	[0.340]	294
male	0.119	[0.168]	−0.098	[0.293]	294
female	−0.040	[0.159]	0.088	[0.317]	294
urban	0.026	[0.146]	−0.115	[0.319]	287
rural	0.127	[0.154]	0.108	[0.266]	277
10 to 18					
1-25 percentile	0.109	[0.059]†	0.161	[0.080]*	293
25-50 percentile	−0.024	[0.080]	0.049	[0.113]	294
50-100 percentile	−0.085	[0.086]	0.011	[0.132]	294
male	0.117	[0.057]*	0.151	[0.078]†	294
female	−0.010	[0.057]	0.100	[0.079]	294
urban	−0.010	[0.069]	0.046	[0.113]	287
rural	0.051	[0.050]	0.146	[0.068]*	277

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Table 5.7: Effect of the JPS scholarships on net enrolment, by per capita consumption, gender and urban/rural (IV estimates for equation (5.3))

Sub group	OLS		IV		
	$\hat{\tau}$	[s.e.]	$\hat{\tau}$	[s.e.]	N
Primary					
1-25 percentile	0.014	[0.046]	0.102	[0.063]	293
25-50 percentile	0.109	[0.060]†	0.108	[0.092]	294
50-100 percentile	0.064	[0.096]	0.104	[0.160]	294
male	0.169	[0.053]**	0.170	[0.076]*	294
female	0.130	[0.053]*	0.189	[0.074]*	294
urban	0.121	[0.077]	0.267	[0.152]†	287
rural	0.034	[0.043]	0.126	[0.058]*	277
Junior Secondary					
1-25 percentile	0.007	[0.047]	0.033	[0.081]	290
25-50 percentile	−0.129	[0.061]*	−0.025	[0.106]	293
50-100 percentile	−0.148	[0.082]†	0.012	[0.162]	294
male	−0.047	[0.061]	0.048	[0.097]	294
female	−0.027	[0.049]	0.003	[0.079]	294
urban	−0.137	[0.068]*	−0.079	[0.123]	287
rural	−0.006	[0.044]	0.031	[0.067]	276
Senior Secondary					
1-25 percentile	−0.044	[0.045]	0.050	[0.112]	275
25-50 percentile	−0.109	[0.062]†	−0.175	[0.149]	292
50-100 percentile	−0.172	[0.111]	−0.182	[0.263]	293
male	−0.004	[0.070]	0.042	[0.143]	294
female	−0.135	[0.065]*	−0.031	[0.149]	294
urban	−0.124	[0.108]	−0.244	[0.316]	286
rural	0.020	[0.049]	0.040	[0.091]	273

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

roughly represents the population that lives of a consumption level below the poverty line.[23]

The results show a very heterogeneous pattern, and suggest that the programme was most effective for those most vulnerable to the crisis. The largest effects are found for children aged 10 to 12 from rural areas who live below the poverty line. This is exactly the group for which investment in education was most affected by households' consumption smoothing during the crisis (Thomas *et al.*, 2004). A similar pattern is found for the 13-15 age group, although the estimates are less precise. Overall, the effect of the scholarships seem to favour boys over girls. For 10-12 year olds the effects are fairly similar for boys and girls, but for children aged 13-15 the scholarships are more effective for boys. For the oldest age group there is no statistically significant effect for any of the population groups, indicating that the absence of an overall effect for this groups is not only due to bad targeting, but that enrolment is also less sensitive to income shocks. Table 5.7 gives the results for net enrolment by age group, confirming that the scholarships are effective only at primary school. The significant and negative OLS estimates further confirm that difference approach in equation (5.3) is not sufficient to deal with the selective targeting of districts.

What would have been the trend in overall enrolment if the JPS scholarship programme had not been implemented? The overall increase of the enrolment rate due to the programme ($\hat{\tau}\overline{T}$) for 10 to 18 year olds is 0.6 percentage point. The trend in the enrolment rate from 1997 to 1999 (table 2.1) shows a slight decrease in 1998 and then a 0.7 percentage point increase a year later. The estimated effect suggests that in the absence of the programme, enrolment would have remained unchanged from 1998 to 1999. Moreover, the JPS has pushed overall enrolment above the pre-crisis level. For children aged 10-12 enrolment decreased by 0.3 percentage point in 1998, and returned to it's pre-crisis level in 1999. The programme increased the enrolment rate by 0.6 percentage point. This means that if the programme had not been implemented, enrolment for this age group would have decreased further in 1999. For the age group 13-15 the increase in enrolment from 1998 to 1999 is 1.7 percentage point, of which about half (0.8 percentage point) is due to the JPS programme.[24]

[23]Due to the number of observations in the intervention group, the analysis had to be restricted to these three per capita consumption groups. A breakdown by quintile was problematic, especially for the non-poor, as the means were based on too few observations, leaving very little variation in the treatment variable.

[24]The JPS programme also included budgetary support to schools. If these grants affected enrolment then the estimates above measure the confounding effect of both components of the programme. This is tested by adding a variable with per capita DBO transfers per district as a regressor. Table 5.14 in appendix 5.B shows that enrolment is not affected by per capita DBO allocation to districts. The estimated effects of scholarships change little (slightly larger) with this specification, suggesting that the

5.4.3 The effect on school attendance and child labour

Estimation

The effect of the JPS scholarship programme on the simultaneous decision regarding school attendance and work activities of enrolled children is analysed at the individual level. Endogenous programme participation is dealt with by using a control function approach.[25] Like standard IV this method requires an exclusion restriction, but it is better suited to deal with unobserved effect heterogeneity. The correlation between unobserved heterogeneity and programme selection is explicitly estimated, instead of relying on strong assumptions about this relationship.

Let A_i^* and L_i^* describe the latent processes that underlie the decision to have an enrolled child attend school ($A_i = 1$) and undertake labour activities ($L_i = 1$). These decisions may be correlated with each other and both may be correlated with the latent variable T_i^*, which describes the decision rule for allocating scholarships to students. Only the outcome of this allocation process is observed, with value $T_i = 1$ if a child receives a scholarship and $T_i = 0$ otherwise. The relationship between programme participation and the outcomes is given by a latent variable model

$$A_i^0 = 1\left[A_i^{*0} \geq 0\right] = 1\left[\beta_a' X_i + u_{ai}^0 \geq 0\right] \tag{5.5a}$$
$$A_i^1 = 1\left[A_i^{*1} \geq 0\right] = 1\left[\beta_a' X_i + \gamma_a T_i + u_{ai}^1 \geq 0\right] \tag{5.5b}$$
$$L_i^0 = 1\left[L_i^{*0} \geq 0\right] = 1\left[\beta_l' X_i + u_{li}^0 \geq 0\right] \tag{5.5c}$$
$$L_i^1 = 1\left[L_i^{*1} \geq 0\right] = 1\left[\beta_l' X_i + \gamma_l T_i + u_{li}^1 \geq 0\right] \tag{5.5d}$$
$$T_i = 1\left[T_i^* \geq 0\right] = 1[\beta_T' X_i + \delta z_j + v_i \geq 0] \tag{5.5e}$$

where $1[\cdot]$ is a binary indicator function. $\left(A_i^{*0}, L_i^{*0}\right)$ are the latent states when a student does not receive a scholarship, and $\left(A_i^{*1}, L_i^{*1}\right)$ if the student does. Selection on unobservables (in the base state) implies that (u_{ai}^0, u_{li}^0) are correlated with v_i. Selection on potential gains means that $\text{cov}\left(u_a^0, v\right) \neq \text{cov}\left(u_a^1, v\right)$ or $\text{cov}\left(u_l^0, v\right) \neq \text{cov}\left(u_l^1, v\right)$. In this specification the effect of the programme enters additively. Observed effect heterogeneity can be introduced by interaction terms of X_i and T_i.

The unobservables $(u_{ai}^0, u_{ai}^1, u_{li}^0, u_{li}^1, v_i)$ are assumed to be independent of z_j and X_i. Note that this is a stronger assumption than that underlying the exclusion restriction with IV. In contrast to standard IV, the instrument now is assumed to be exogenous to the allocation of scholarships. For the targeting error $\hat{z}_j$ this is a reasonable assumption.

block grants do not interfere with the estimates of the scholarships.

[25] See Heckman and Navarro-Lozano (2004) for a discussion on control function methods.

Assume further that the unobservables have a joint standard normal distribution

$$\begin{bmatrix} u_a^0 \\ u_a^1 \\ u_l^0 \\ u_l^1 \\ v \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_a & \rho_{al0} & \rho_{01} & \rho_{a0} \\ \rho_a & 1 & \rho_{10} & \rho_{al1} & \rho_{a1} \\ \rho_{al0} & \rho_{10} & 1 & \rho_l & \rho_{l0} \\ \rho_{01} & \rho_{al1} & \rho_l & 1 & \rho_{l1} \\ \rho_{a0} & \rho_{a1} & \rho_{l0} & \rho_{l1} & 1 \end{bmatrix} \right)$$

The outcomes that we actually observe are

$$A_i = 1\left[A_i^* \geq 0\right] = 1\left[A_i^{*1} T_i + A_i^{*0}(1 - T_i) \geq 0\right] \tag{5.6a}$$

$$L_i = 1\left[L_i^* \geq 0\right] = 1\left[L_i^{*1} T_i + L_i^{*0}(1 - T_i) \geq 0\right] \tag{5.6b}$$

where the conditional expectations of the latent outcomes are

$$\begin{aligned} E\left(A_i^* \mid X_i, z_j\right) &= \beta_a' X_i + \gamma_a T_i + T_i E\left(u_{ai}^1 \mid T_i = 1\right) \\ &\quad + (1 - T_i) E\left(u_{ai}^0 \mid T_i = 0\right) \end{aligned} \tag{5.7a}$$

$$\begin{aligned} E\left(L_i^* \mid X_i, z_j\right) &= \beta_l' X_i + \gamma_l T_i + T_i E\left(u_{li}^1 \mid T_i = 1\right) \\ &\quad + (1 - T_i) E\left(u_{li}^0 \mid T_i = 0\right) \end{aligned} \tag{5.7b}$$

Given the normality assumption, the conditional expectations of $(u_{ai}^0, u_{ai}^1, u_{li}^0, u_{li}^1)$ in equations (5.7a) and (5.7b) are

$$\begin{aligned} E[u_{ai}^0 &\mid T_i = 0] = E[u_{ai}^0 \mid v_i < -(\varphi' X_i + \delta z_j)] = \rho_{a0}\lambda_{0i} \\ E[u_{ai}^1 &\mid T_i = 1] = E[u_{ai}^1 \mid v_i \geq -(\varphi' X_i + \delta z_j)] = \rho_{a1}\lambda_{1i} \\ E[u_{li}^0 &\mid T_i = 0] = E[u_{li}^0 \mid v_i < -(\varphi' X_i + \delta z_j)] = \rho_{l0}\lambda_{0i} \\ E[u_{li}^1 &\mid T_i = 1] = E[u_{li}^1 \mid v_i \geq -(\varphi' X_i + \delta z_j)] = \rho_{l1}\lambda_{1i} \end{aligned}$$

where

$$\lambda_{0i} = \frac{-\phi(\varphi' X_i + \delta z_j)}{1 - \Phi(\varphi' X_i + \delta z_j)}, \qquad \lambda_{1i} = \frac{\phi(\varphi' X_i + \delta z_j)}{\Phi(\varphi' X_i + \delta z_j)}$$

and ϕ and Φ denote the standard normal df and cdf, respectively. The inverse Mills ratio's λ_0 and λ_1 are computed from (consistent) first stage probit estimates of (5.5e). This provides an empirical specification for (5.6a) and (5.6b)

$$A_i = 1\left[\beta_a' X_i + \gamma_a T_i + \rho_{a1}\lambda_{1i} T_i + \rho_{a0}\lambda_{0i}(1 - T_i) + \varepsilon_{ai} \geq 0\right] \tag{5.8a}$$

$$L_i = 1\left[\beta_l' X_i + \gamma_l T_i + \rho_{l1}\lambda_{1i} T_i + \rho_{l0}\lambda_{0i}(1 - T_i) + \varepsilon_{li} \geq 0\right] \tag{5.8b}$$

In this switching regression framework the selection terms capture the bias due to endogenous programme participation trough the parameters $(\rho_{a0}, \rho_{a1}, \rho_{l0}, \rho_{l1})$. Selection on unobservables (in the base state) implies $\rho_{a0} \neq 0$ or $\rho_{l0} \neq 0$. Selection on potential gains is evaluated by testing $\rho_{a0} = \rho_{a1}$ and $\rho_{l0} = \rho_{l1}$. Note that $(\rho_a, \rho_l, \rho_{01}, \rho_{10})$ are not identified, since we never observe the outcomes of an individual child in both states.

Under the normality assumption, equations (5.8a) and (5.8b) can be estimated as a bivariate probit, with $(\varepsilon_{ai}, \varepsilon_{li}) \sim N(0, \Sigma)$. The simultaneous nature of labour and schooling decisions is now expressed by the parameter $\rho = corr(\varepsilon_{ai}, \varepsilon_{li})$.[26]

The average effects of the scholarships are calculated as

$$\Pr\left(A^1 = 1\right) - \Pr\left(A^0 = 1\right) = \Phi\left(\beta_a' X + \gamma_a T\right) - \Phi\left(\beta_a' X\right) \quad (5.9a)$$

$$\Pr\left(L^1 = 1\right) - \Pr\left(L^0 = 1\right) = \Phi\left(\beta_l' X + \gamma_l T\right) - \Phi\left(\beta_l' X\right) \quad (5.9b)$$

which are the marginal effects of γ_a and γ_l.

Results

The bivariate probit estimates for the effect of JPS scholarships on school attendance and child labour are summarised by age group in table 5.8. The table provides the estimated treatment parameters and correlation coefficients.

The scholarship variable T_i is interacted with gender, per capita consumption group, and a rural area dummy variable. The covariates further include age, household size, main source of household income (agriculture/non-agriculture), head of household characteristics (gender and level of education) and a variable indicating whether the child goes to public or private school. The specification also includes regional welfare indicators P_0, P_1, $BPS96$, the BKKBN poverty estimates for districts and sub-districts, IDT status of the village, and 6 variables indicating the presence of schools in the village (primary, junior secondary, and senior secondary, by public/private). Finally, the model includes a set of province dummy variables.[27] For convenience, the coefficients for covariates are omitted from the table. The first stage probit (5.5e) includes the same covariates and $JPS96$ as instrument. With P_0, P_1 and $BPS96$ controlling for non-random geographic targeting, $JPS96$ reflects the mis-targeting residual. The $JPS96$ coefficient is positive and significant at a 1 percent level for all age groups. As poverty is overestimated in the geographic targeting stage the probability of receiving a scholarship increases.[28]

[26] This implicitly assumes that correlation between u_a and u_l is constant between treatment states (i.e., $\rho = \rho_{al0} = \rho_{al1}$).

[27] In 1999 Indonesia counted 27 provinces.

[28] The first stage probit estimates are given in detail in table 5.15 in appendix 5.B.

Overall, the scholarships do have an effect on school attendance and child labour. Although not all coefficients are statistically significant, they are jointly significant for both outcomes. The test statistic for joint significance is given in row 8 of each panel. Looking at the different age groups, the treatment parameters are always jointly significant for labour. For school attendance there seems to be only an effect for students aged 13 to 15.

There is some evidence of selection on unobservables (indicated by ρ_0). Especially for labour of the older students there is a strong correlation between u_{li}^0 and v_i. The results also suggest that students are selected based on potential gains from the programme, as the hypothesis that $\rho_0 = \rho_1$ is rejected. Again, for labour this result is stronger. The schooling and labour decisions of students are not independent, given the covariates. The correlation coefficient ρ is significant at a 1 percent level. The correlation between both decisions is negative and becomes stronger with age (varying from -0.20 to -0.34).[29]

The average effects are given in table 5.9. Starting with the aggregate effects of the scholarships, the probability of attending school in the previous week is 1.5 percentage point higher for students with a scholarship than for non-recipients. This seems a small change in nominal terms, but given attendance rates of around 98 percent (table 5.1) this implies that non-attendance has decreased by about 38 percent relative to the counterfactual situation of no JPS programme. The effect on child labour is larger, with the probability of working decreasing by 3.8 percentage point for students with a scholarship. This suggests that the programme reduced the incidence of child work from 14.0 to 10.2 percent, a 27 percent decrease relative to the base state (see table 5.2).

These results suggest that the scholarships reduced the need for child labour to smooth household income during the crisis, raising the reservation wage for students. Note that labour supply seems to be more sensitive to the programme than school attendance. Increased school attendance takes account of at most half of the time reallocated away from labour activities.

The absolute size of the effects on labour increase with age. This results is in part due to the fact that the incidence of child labour is higher amongst older students. Also, the size of the scholarships increases with enrolment level. For the youngest age group (10-12) the probability of working is reduced by 1.7 percentage point (20 percent relative decrease). For students aged 13-15 the effect on labour is larger, at 5.1 percentage point (30 percent relative decrease). For the oldest students a scholarship decreases the probability of working by 10.0 percentage point (40 percent relative decrease).

[29] This follows Canagarajah and Coulombe (1997) and Nielsen (1998), who also analyse the joint decision of school attendance and child labour with a bivariate probit. Both studies find a negative and statistically significant correlation coefficient.

Table 5.8: Bivariate probit estimates for the effect of JPS scholarships on school attendance and child labour, conditional on enrolment (equations (5.8a) and (5.8b))

Age group	Parameter	School attendance		Child labour	
		Coefficient	[s.e.][1]	Coefficient	[s.e.][1]
10 to 12	γ	0.569	[0.365]	0.041	[0.222]
N=48,798	$\gamma_{1-25\,pctile}$	−0.092	[0.123]	0.018	[0.101]
ρ= -0.197**	$\gamma_{25-50\,pctile}$	0.037	[0.139]	−0.166	[0.103]
	γ_{female}	−0.129	[0.103]	0.046	[0.077]
	γ_{rural}	−0.115	[0.166]	−0.333	[0.123]**
	ρ_1	−0.207	[0.135]	0.213	[0.101]*
	ρ_0	0.064	[0.184]	0.205	[0.159]
	Test joint sig. γ, $\chi^2(5)$	4.16		14.69*	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	1.91		0.00	
13 to 15	γ	0.719	[0.350]*	−0.229	[0.187]
N=39,561	$\gamma_{1-25\,pctile}$	−0.121	[0.130]	−0.117	[0.064]*
ρ=-0.331**	$\gamma_{25-50\,pctile}$	0.035	[0.141]	−0.081	[0.074]
	γ_{female}	−0.186	[0.106]†	−0.060	[0.057]
	γ_{rural}	0.027	[0.132]	−0.113	[0.092]
	ρ_1	−0.345	[0.148]*	0.245	[0.083]**
	ρ_0	−0.047	[0.214]	0.573	[0.156]**
	Test joint sig. γ, $\chi^2(5)$	11.05*		17.13**	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	2.48		5.56*	
16 to 18	γ	0.749	[0.592]	−0.883	[0.288]**
N=24,828	$\gamma_{1-25\,pctile}$	0.015	[0.222]	−0.135	[0.105]
ρ=-0.343**	$\gamma_{25-50\,pctile}$	−0.081	[0.585]	−0.093	[0.115]
	γ_{female}	0.040	[0.177]	−0.125	[0.095]
	γ_{rural}	−0.123	[0.206]	0.087	[0.106]
	ρ_1	−0.238	[0.265]	0.470	[0.119]**
	ρ_0	−0.330	[0.363]	0.863	[0.263]**
	Test joint sig. γ, $\chi^2(5)$	3.33		18.97**	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	0.06		2.60	
10 to 18	γ	0.627	[0.230]**	−0.213	[0.137]
N=113,187	$\gamma_{1-25\,pctile}$	−0.092	[0.087]	−0.075	[0.052]
ρ=-0.295**	$\gamma_{25-50\,pctile}$	0.025	[0.087]	−0.104	[0.048]*
	γ_{female}	−0.122	[0.060]*	−0.034	[0.043]
	γ_{rural}	−0.071	[0.087]	−0.113	[0.060]†
	ρ_1	−0.245	[0.094]**	0.242	[0.061]**
	ρ_0	−0.006	[0.129]	0.483	[0.124]**
	Test joint sig. γ, $\chi^2(5)$	11.99*		27.18**	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	3.41†		5.80*	

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

[1] Bootstrapped standard errors with 100 replications

Table 5.9: Average effects of JPS scholarships on school attendance and child labour, conditional on enrolment (equations (5.9a) and (5.9b))

Age group	Sub group	School attendance		Child labour	
		ATE	[s.e.][1]	ATE	[s.e.][1]
10 to 12	Average	0.012	[0.006]*	−0.017	[0.010]†
	1-25 percentile	0.010	[0.006]	−0.019	[0.014]
	25-50 percentile	0.014	[0.006]*	−0.022	[0.008]**
	50-100 percentile	0.011	[0.006]*	−0.012	[0.010]
	Male	0.013	[0.005]*	−0.020	[0.012]†
	Female	0.010	[0.006]	−0.013	[0.009]
	Urban	0.010	[0.005]*	0.001	[0.007]
	Rural	0.012	[0.006]*	−0.024	[0.012]*
13 to 15	Average	0.018	[0.005]**	−0.051	[0.017]**
	1-25 percentile	0.020	[0.007]**	−0.076	[0.022]**
	25-50 percentile	0.019	[0.005]**	−0.055	[0.017]**
	50-100 percentile	0.017	[0.004]**	−0.038	[0.016]*
	Male	0.019	[0.005]**	−0.056	[0.021]**
	Female	0.017	[0.006]**	−0.047	[0.014]**
	Urban	0.011	[0.003]**	−0.017	[0.009]†
	Rural	0.022	[0.006]**	−0.069	[0.022]**
16 to 18	Average	0.022	[0.018]	−0.100	[0.018]**
	1-25 percentile	0.034	[0.019]†	−0.149	[0.027]**
	25-50 percentile	0.025	[0.025]	−0.112	[0.020]**
	50-100 percentile	0.019	[0.016]	−0.085	[0.017]**
	Male	0.022	[0.017]	−0.114	[0.023]**
	Female	0.023	[0.019]	−0.086	[0.014]**
	Urban	0.015	[0.016]	−0.053	[0.009]**
	Rural	0.029	[0.021]	−0.147	[0.028]**
10 to 18	Average	0.015	[0.004]**	−0.038	[0.010]**
	1-25 percentile	0.015	[0.005]**	−0.040	[0.009]**
	25-50 percentile	0.018	[0.004]**	−0.039	[0.008]**
	50-100 percentile	0.017	[0.005]**	−0.033	[0.010]**
	Male	0.016	[0.004]**	−0.042	[0.013]**
	Female	0.014	[0.004]**	−0.033	[0.009]**
	Urban	0.011	[0.003]**	−0.014	[0.006]*
	Rural	0.017	[0.005]**	−0.051	[0.013]**

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The calculated average effects are based on estimation results reported in table (5.8)

[1] Bootstrapped standard errors with 100 replications

Table 5.10: Bivariate probit estimates for the effect of JPS scholarships on school attendance and child labour, conditional on net enrolment (equations (5.8a) and (5.8b))

Level	Parameter	School attendance		Child labour	
		Coefficient	[s.e.][1]	Coefficient	[s.e.][1]
Primary	γ	0.779	[0.609]	−0.011	[0.279]
N=46,253	$\gamma_{1-25\,pctile}$	−0.105	[0.140]	−0.021	[0.107]
ρ= -0.190**	$\gamma_{25-50\,pctile}$	0.095	[0.161]	−0.184	[0.112]
	γ_{female}	−0.067	[0.118]	0.017	[0.072]
	γ_{rural}	−0.287	[0.504]	−0.272	[0.126]*
	ρ_1	−0.255	[0.150]†	0.239	[0.116]*
	ρ_0	0.043	[0.194]	0.220	[0.183]
	Test joint sig. γ, $\chi^2(5)$	6.57		10.86†	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	2.27		0.01	
Junior Secondary	γ	1.049	[0.431]**	−0.552	[0.243]*
N=27,840	$\gamma_{1-25\,pctile}$	−0.157	[0.169]	−0.064	[0.089]
ρ=-0.326**	$\gamma_{25-50\,pctile}$	−0.024	[0.164]	−0.046	[0.090]
	γ_{female}	−0.097	[0.136]	−0.104	[0.071]
	γ_{rural}	0.112	[0.158]	−0.124	[0.084]
	ρ_1	−0.541	[0.183]**	0.421	[0.111]**
	ρ_0	−0.445	[0.251]†	0.688	[0.185]**
	Test joint sig. γ, $\chi^2(5)$	13.65*		23.52**	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	0.15		2.48†	
Senior Secondary	γ	0.788	[1.310]	−1.138	[0.541]*
N=17,911	$\gamma_{1-25\,pctile}$	0.079	[1.145]	0.090	[0.184]
ρ=-0.261**	$\gamma_{25-50\,pctile}$	0.066	[0.709]	−0.094	[0.152]
	γ_{female}	−0.302	[0.549]	−0.192	[0.140]
	γ_{rural}	0.051	[0.898]	0.220	[0.162]
	ρ_1	−0.150	[0.410]	0.512	[0.224]*
	ρ_0	−1.670	[0.668]*	1.738	[0.424]**
	Test joint sig. γ, $\chi^2(5)$	3.05		12.39*	
	Test $\rho_0 = \rho_1$, $\chi^2(1)$	6.13*		9.96**	

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

[1] Bootstrapped standard errors with 100 replications

Table 5.11: Average effects of JPS scholarships on school attendance and child labour, conditional on net enrolment (equations (5.9a) and (5.9b))

Level	Sub group	School attendance		Child labour	
		ATE	[s.e.][1]	ATE	[s.e.][1]
Primary	Average	0.013	[0.005]**	−0.018	[0.013]
	1-25 percentile	0.011	[0.006]†	−0.022	[0.016]
	25-50 percentile	0.017	[0.006]**	−0.023	[0.010]*
	50-100 percentile	0.013	[0.005]*	−0.012	[0.013]
	Male	0.014	[0.005]**	−0.022	[0.015]
	Female	0.012	[0.005]*	−0.015	[0.011]
	Urban	0.012	[0.003]**	−0.001	[0.008]
	Rural	0.014	[0.006]*	−0.025	[0.015]†
Junior Secondary	Average	0.023	[0.004]**	−0.077	[0.016]**
	1-25 percentile	0.028	[0.007]**	−0.106	[0.022]**
	25-50 percentile	0.026	[0.005]**	−0.085	[0.018]**
	50-100 percentile	0.021	[0.004]**	−0.063	[0.015]**
	Male	0.023	[0.004]**	−0.085	[0.020]**
	Female	0.024	[0.005]**	−0.069	[0.013]**
	Urban	0.013	[0.003]**	−0.030	[0.008]**
	Rural	0.030	[0.005]**	−0.106	[0.022]**
Senior Secondary	Average	0.022	[0.048]	−0.101	[0.028]**
	1-25 percentile	0.038	[0.036]	−0.130	[0.043]**
	25-50 percentile	0.028	[0.048]	−0.121	[0.030]**
	50-100 percentile	0.018	[0.051]	−0.091	[0.027]**
	Male	0.024	[0.032]	−0.112	[0.034]**
	Female	0.021	[0.065]	−0.090	[0.023]**
	Urban	0.016	[0.052]	−0.062	[0.016]**
	Rural	0.030	[0.045]	−0.151	[0.046]**

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

The calculated average effects are based on estimation results reported in table (5.10)

[1] Bootstrapped standard errors with 100 replications

The effects vary with the characteristics of the students. Generally, the effects on labour were largest for students from poor households, in rural areas, and for boys. This suggest that reservation wages are lower for the poor, and in rural areas. The fact that labour supply is more responsive for boys may reflect the fact that boys are more often engaged in own farm and wage labour, while girls may be more committed to domestic work. This pattern is seen for all but the youngest age groups. The biggest differences are found for urban and rural areas. The probability of working in rural areas decreased by 5.1 percentage point, against 1.4 in urban areas. In case of school attendance the differences in the effects are smaller and often not significant, except for the urban-rural differential. The effect on school attendance is larger in rural areas.

The bivariate probit estimates and average effects by (net) enrolment level are given in tables 5.10 and 5.11 show similar results.

Finally, a remark about possible external effects of the scholarships within the households. Because the cash transfers relax the budget constraint for the whole households, the scholarship of one students may have positive spillover effects on siblings that were not selected into the programme. If this is the case then the estimated treatment effects may be biased because observations are no longer independent. The appendix 5.A investigates the robustness of the bivariate probit estimates. The overall conclusion is that the estimates seem not to be contaminated by confounding spillover effects. The exception is school attendance for children age 10 to 12, which seems to be sensitive to the independence assumption. School attendance for the youngest is increased if a brother or sister has received a scholarship.

5.5 Conclusion

This chapter analyses the effectiveness of the Indonesian Social Safety Net scholarship programme, which was introduced in August 1998 to protect the educational sector during the East Asian economic crisis. The programme appears to have been effective in protecting access to education, despite considerable problems concerning geographical targeting in the initial year.

The impact of the programme is identified by exploiting the decentralised structure of the programme design and the fact that at the initial stage of the programme only incomplete information on the effects of the crisis was available to policy makers. This incomplete information on regional poverty gave rise to some geographic mis-targeting. Instrumental variables are constructed from this mis-targeting, using data on the selection rules and ex-post information on the regional poverty profile. The availability of pre-intervention data makes it possible to verify the credibility of the identifying assumptions and the validity of the instrument.

Without the JPS programme enrolment would have dropped substantially, especially in primary school. Ten percent of programme participants between 10 and 12 years old would have dropped out of school if they had not received a scholarship. In absence of the programme, the enrolment rate for this group would have been 0.6 percentage point lower. This suggests that the programme has actually prevented enrolment to decrease from 1998 to 1999. For the age group 13-15 the programme increased the enrolment rate by 0.8 percentage point, although these estimates are not precise. This would account for half of the observed increase in enrolment. However, most of this effect concerns children in primary school. This is an important result because this is the age group where, in general, the transition from primary to junior secondary school takes place. It is at this transition point that many students leave school. Amongst children aged 16 to 18 no significant effect was found. These results suggest that secondary school scholarships did little to affect enrolment.

The scholarships were especially effective for children whose education attainment was most vulnerable to the effects of the crisis. In response to the crisis, poor rural households facing resource constraints reduced investment in education of the youngest children in the household for consumption smoothing reasons, and protected the education of older children (Thomas *et al.*, 2004). This reflects the differences in future earnings from secondary and primary education, the fact that households have already invested in secondary education of older children, and the relatively low secondary school enrolment amongst students from poor families. Accordingly, the strongest effects of the scholarships were found amongst children at primary school in rural areas, from households that live below the poverty line.

The JPS programme also affected the decisions regarding school attendance and labour activities of enrolled children. Scholarship recipients were more likely to go to school and less likely to work. Although it was not an explicit goal of the programme, the scholarships raised the reservation wage for students. The cash transfers relieved the pressure on households to draw on the labour of their children to smooth income. The effects on child labour are largest for the poor, suggesting that reservation wages for the poor are lower than for the non-poor.

Labour supply is much more sensitive to programme participation than school attendance, in absolute terms. This result differs from studies by Ravallion and Wodon (2000), Skoufias and Parker (2001) and Schultz (2004), who find that increased schooling is only partly explained by a reduction in labour. The difference in these results is most likely explained by the extreme setting of the South-east Asian economic crisis. Under these circumstances the pressure on households to draw on child labour strongly increased. The estimation results then suggest that this came only partly at the expense of school attendance. This supports the notion by Suryahadi *et al.* (2005) that schooling and part time work often go together in Indonesia.

Concluding, the JPS scholarships have proved to be an effective instrument for protecting access to education. On the other hand, the allocation committees appear to have been only partly capable of identifying the poor. A large part of the funds have been allocated to students who would not have dropped out of school. More accurate targeting would greatly improve the programme's effectiveness. Furthermore, priority should have been placed on protecting primary school enrolment, where the scholarships seem most effective, and with providing support for children from the poorest households in the transition from primary to secondary schooling.

5.A Spillover effects

The JPS scholarships are cash transfers to children. These transfers relax the households budget constraint. Children that did not receive scholarships but have a sibling that does, may therefore still benefit from the programme. If this is the case then the estimated treatment effects may be biased downward.

To analyse the extent of the bias, I re-estimate the treatment effects for different sub-samples. In particular, I compare students that received a scholarship but their sibling not ($T = 1, S = 0$), students that did not receive a scholarship but their sibling did ($T = 0, S = 1$), and students from households where nobody received a scholarship ($T = 0, S = 0$). These students have three possible outcomes (Y):

1. $T = 1, S = 0: \quad Y^{10} = \alpha_0 + \beta_T T + u^{10}$
2. $T = 0, S = 1: \quad Y^{01} = \alpha_0 + \beta_S S + u^{01}$
3. $T = 0, S = 0: \quad Y^{00} = \alpha_0 + u^{00}$

where u is the unobserved component, and α_0 the base state. The spillover effects of scholarships cause the estimated treatment effect to be biased by contaminating the control group through $\beta_S S$ in sub-sample 2. Therefore, a switching regression model is estimated for groups 1 and 3 to find the treatment effect

$$E[Y] = \alpha_0 + \beta_T T + TE[u^{10} \mid T = 1] + (1 - T)\, E[u^{00} \mid T = 0]$$

and groups 2 and 3 to find the spillover effect

$$E[Y] = \alpha_0 + \beta_S S + SE[u^{01} \mid S = 1] + (1 - S)\, E[u^{00} \mid S = 0]$$

With a binary outcome Y, the average treatment effect (Δ_T) and spillover effect (Δ_S) are calculated as

$$\begin{aligned}\Delta_T &= \Pr\left(Y^{10} = 1\right) - \Pr\left(Y^{00} = 1\right) = \Phi\left(\alpha_0 + \beta_T T\right) - \Phi\left(\alpha_0\right) \\ \Delta_S &= \Pr\left(Y^{01} = 1\right) - \Pr\left(Y^{00} = 1\right) = \Phi\left(\alpha_0 + \beta_S S\right) - \Phi\left(\alpha_0\right)\end{aligned}$$

The results are given in table 5.12 below. For ease of comparison the estimated treatment effect using the full sample (copied from table 5.9) is also reported in the table, indicated by Δ_T^*. Except for the choice of sub-sample, the estimation procedure and specification are identical to that in section 5.4.

The estimates for child work do not seem to be effected by spillover effects. For all age groups the treatment effects (Δ_T^* and Δ_T) are very similar. The spillover effect on working has a negative sign: children are less likely to work if their brother or sister has received a scholarship. However, the estimates are not statistically significant for children younger than 16. For older children the estimated spillover effect is statistically significant. There is no statistically significant spillover effect of scholarships on school attendance, for any age group. Nevertheless, the results for school attendance are a more sensitive to the choice of sub-sample than for work activities. For 10 to 12 year olds the estimate of Δ_T is smaller end less precise than Δ_T^*. For the other age groups the results are more robust.

Overall, the estimates and interpretation of the results seem not to be contaminated by confounding spillover effects. There is no evidence of underestimated treatment effects when using the full sample.

Table 5.12: Test for spillover effects (by age group)

Age group	ATE	Attendance	[s.e.]	Work	[s.e.]	N
10-12						
	Δ_T^*	0.012	[0.006]*	-0.017	[0.010]†	48,798
	Δ_T	0.002	[0.013]	-0.016	[0.015]	46,306
	Δ_S	0.013	[0.008]	-0.003	[0.038]	45,668
13-15						
	Δ_T^*	0.018	[0.005]**	-0.051	[0.017]**	39,561
	Δ_T	0.013	[0.009]	-0.049	[0.023]*	37,556
	Δ_S	-0.007	[0.038]	-0.015	[0.057]	35,910
16-18						
	Δ_T^*	0.022	[0.018]	-0.100	[0.018]**	24,828
	Δ_T	0.022	[0.013]†	-0.114	[0.021]**	23,695
	Δ_S	0.020	[0.031]	-0.101	[0.038]**	23,539
10-18						
	Δ_T^*	0.015	[0.004]**	-0.038	[0.010]**	113,187
	Δ_T	0.008	[0.006]	-0.034	[0.013]**	107,557
	Δ_S	0.011	[0.009]	-0.039	[0.018]**	105,117

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

5.B Supplementary tables

Table 5.13: Effect of the JPS scholarships on enrolment, controlling for "no-treatment" districts

Age group	$\hat{\tau}$	[s.e.]	$\hat{\theta}_{no-treat}$	[s.e.]	N
OLS					
10 to 12	0.074	[0.026]**	-0.002	[0.008]	294
13 to 15	0.021	[0.052]	-0.022	[0.017]	294
16 to 18	0.083	[0.147]	0.010	[0.013]	294
10 to 18	0.054	[0.048]	0.002	[0.018]	294
IV					
10 to 12	0.100	[0.037]**	-0.000	[0.008]	294
13 to 15	0.106	[0.077]	-0.016	[0.017]	294
16 to 18	0.031	[0.261]	0.009	[0.015]	294
10 to 18	0.130	[0.066]†	0.007	[0.019]	294

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Table 5.14: Effect of the JPS scholarships on enrolment, controlling for per capita DBO transfers

Age group	$\hat{\tau}$	[s.e.]	$\hat{\tau}_{DBO}$	[s.e.]	N
OLS					
10 to 12	0.086	[0.028]**	-0.001	[0.001]	294
13 to 15	0.036	[0.053]	0.000	[0.004]	294
16 to 18	0.067	[0.142]	-0.003	[0.004]	294
10 to 18	0.053	[0.051]	-0.000	[0.001]	294
IV					
10 to 12	0.117	[0.040]**	-0.001	[0.001]	294
13 to 15	0.127	[0.081]	-0.002	[0.004]	294
16 to 18	0.035	[0.249]	-0.003	[0.004]	294
10 to 18	0.140	[0.074]†	-0.000	[0.001]	294

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Table 5.15: First stage probit estimates, probability of receiving a JPS scholarship

Variable	10-18		10-12		13-15		16-18	
	Coefficient	[s.e.]	Coefficient	[s.e.]	Coefficient	[s.e.]	Coefficient	[s.e.]
Age	0.035	[0.003]**	0.154	[0.012]**	0.029	[0.012]	−0.035	[0.018]†
Female	0.102	[0.012]**	0.128	[0.019]**	0.090	[0.019]*	0.076	[0.029]**
Public school	0.099	[0.017]**	0.045	[0.034]	0.078	[0.024]**	0.130	[0.033]**
Female head of household	0.332	[0.020]**	0.390	[0.033]**	0.315	[0.032]**	0.278	[0.046]**
Education head of household								
None (= reference)								
Primary	−0.084	[0.014]**	−0.057	[0.022]**	−0.102	[0.022]**	−0.101	[0.036]**
Junior seconadry	−0.206	[0.021]**	−0.147	[0.035]**	−0.206	[0.033]**	−0.245	[0.047]**
Senior secondary	−0.364	[0.024]**	−0.351	[0.042]**	−0.325	[0.037]**	−0.441	[0.053]**
Tertiary	−0.488	[0.045]**	−0.566	[0.095]**	−0.488	[0.069]**	−0.438	[0.082]**
Ln(household size)	−0.014	[0.021]	−0.046	[0.034]	−0.046	[0.033]	0.035	[0.046]
Agriculture main income source	0.063	[0.015]**	0.107	[0.025]**	0.035	[0.024]	0.028	[0.038]
Per capita expenditure								
1-25 pctile	0.298	[0.017]**	0.318	[0.028]**	0.292	[0.027]**	0.283	[0.041]**
25-50 pctile	0.195	[0.016]**	0.215	[0.026]**	0.200	[0.025]**	0.125	[0.036]**
50-100 pctile (= reference)								
$JPS96$ targeting rule	4.589	[0.131]**	4.847	[0.206]**	4.830	[0.207]**	3.717	[0.306]**
District poverty profile								
Poverty headcount (P_0)	−0.030	[0.083]	−0.137	[0.131]	0.018	[0.130]	0.181	[0.206]
Poverty gap (P_1)	0.309	[0.064]**	0.409	[0.102]**	0.203	[0.100]*	0.378	[0.148]**

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... table 5.15 continued

Variable	10-18		10-12		13-15		16-18	
	Coefficient	[s.e.]	Coefficient	[s.e.]	Coefficient	[s.e.]	Coefficient	[s.e.]
1996 headcount (BPS)	−0.588	[0.120]**	−0.672	[0.191]**	−0.708	[0.190]**	−0.243	[0.283]
BKKBN rate district	−0.446	[0.068]**	−0.473	[0.110]**	−0.431	[0.105]**	−0.588	[0.159]**
BKKBN rate sub-district	0.445	[0.041]**	0.408	[0.064]**	0.437	[0.065]**	0.608	[0.098]**
Village								
IDT village	0.075	[0.016]**	0.074	[0.024]**	0.067	[0.025]**	0.091	[0.040]*
Rural area	0.023	[0.019]	−0.021	[0.032]	0.035	[0.030]	0.002	[0.042]
Public primary school	0.084	[0.030]**	0.083	[0.047]†	0.052	[0.047]	0.166	[0.071]*
Private primary school	0.011	[0.014]	0.002	[0.023]	0.026	[0.022]	−0.025	[0.033]
Public jun. sec. school	0.013	[0.015]	−0.023	[0.025]	0.027	[0.024]	0.049	[0.034]
Private jun. sec. school	0.045	[0.017]**	−0.013	[0.027]	0.089	[0.026]**	0.044	[0.038]
Public sen. sec. school	−0.007	[0.021]	0.094	[0.037]*	−0.046	[0.033]	−0.060	[0.044]
Private sen. sec. school	−0.066	[0.020]**	−0.071	[0.035]*	−0.078	[0.031]*	−0.019	[0.043]
Constant	−3.241	[0.083]**	−4.544	[0.177]**	−2.943	[0.203]**	−2.259	[0.029]**
Province fixed effects	yes		yes		yes		yes	
Observations	113,187		48,798		39,561		24,828	
Pseudo R-squared	0.131		0.142		0.130		0.131	

Robust standard errors in brackets.

5.C Supplementary figures

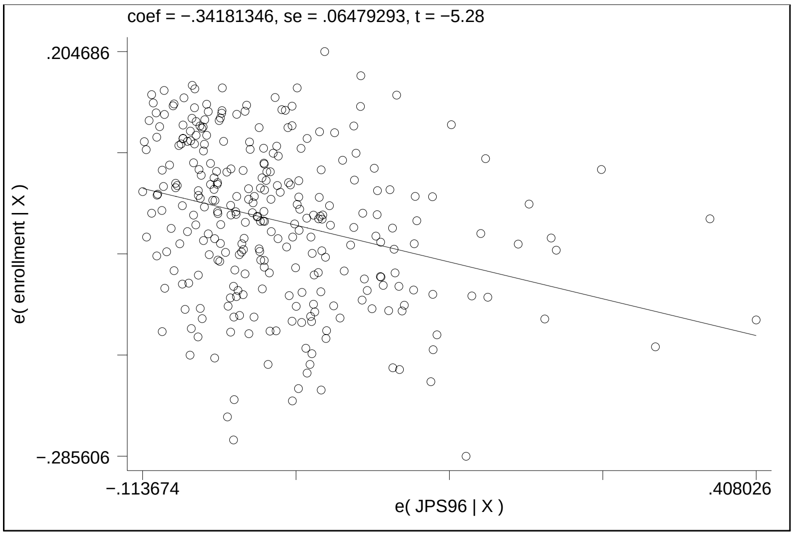

Figure 5.2: Correlation between $JPS96_j$ and enrolment (1998 district means).

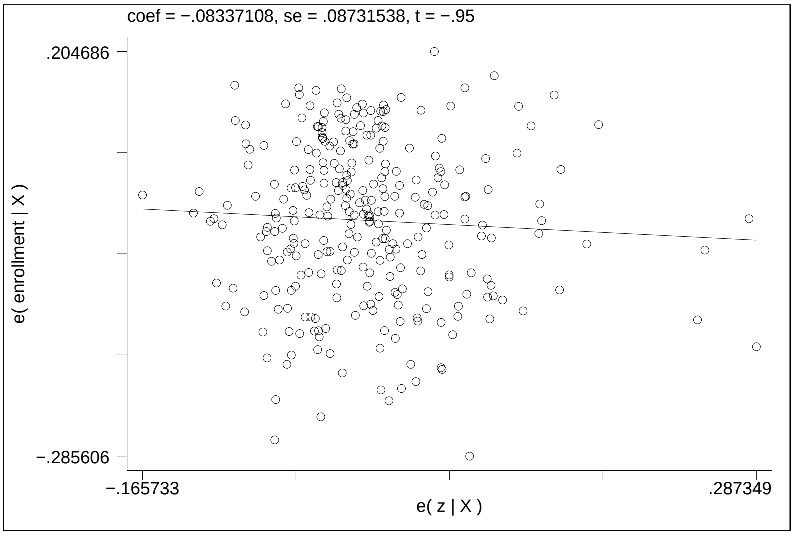

Figure 5.3: Correlation between $\hat{z}_j$ and enrolment (1998 district means).

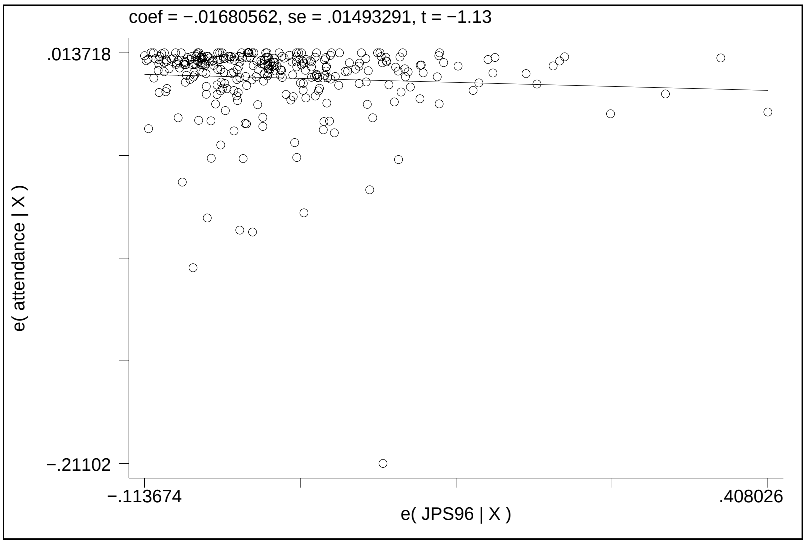

Figure 5.4: Correlation between $JPS96_j$ and school attendance (1998 district means).

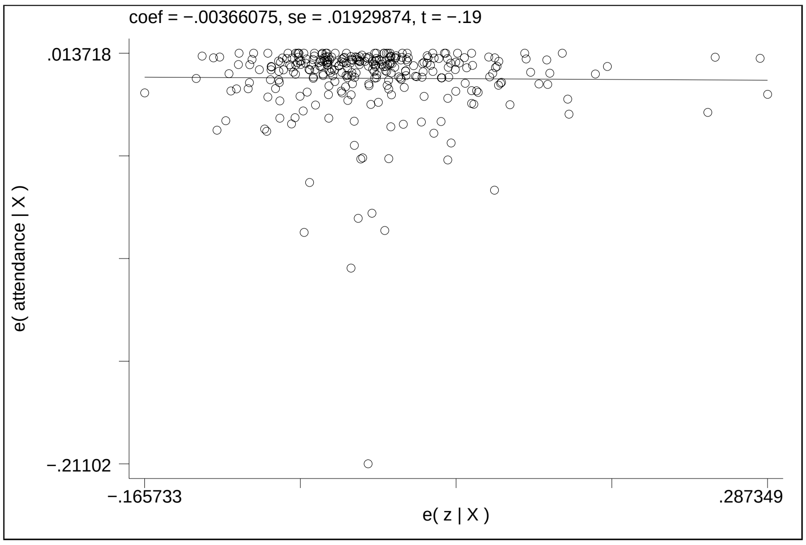

Figure 5.5: Correlation between $\hat{z}_j$ and school attendance (1998 district means).

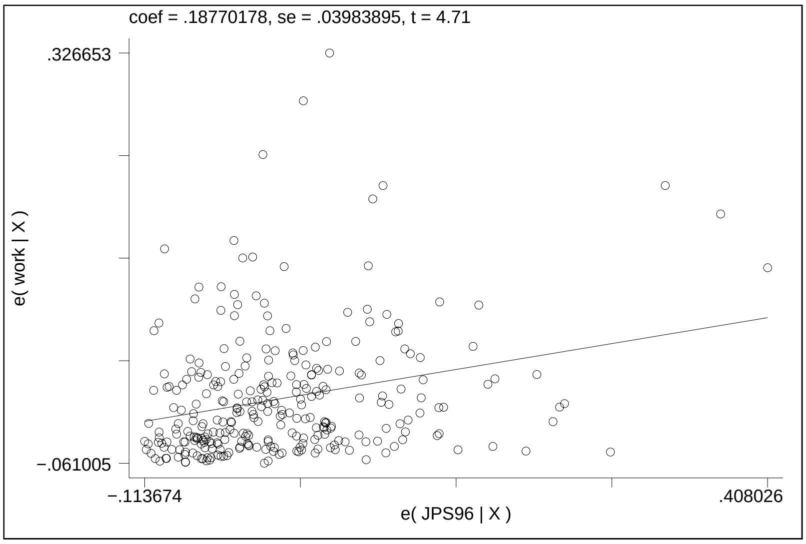

Figure 5.6: Correlation between $JPS96_j$ and child labour (1998 district means).

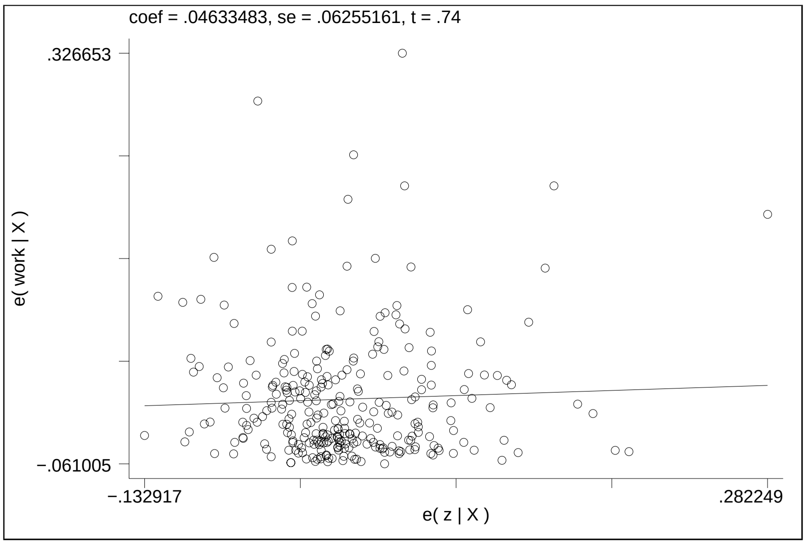

Figure 5.7: Correlation between $\hat{z}_j$ and child labour (1998 district means).

Chapter 6

Did the Health Card Programme Ensure Access to Medical Care for the Poor During Indonesia's Economic Crisis?

6.1 Introduction

In the current debate on the provision of health care services in developing countries, many authors have found high inequalities in the utilisation of public health care and hence the benefit incidence of public spending. Health spending is generally found not to be pro-poor, as public policy typically lacks the incentives for health care providers to serve the poor. Ensuring that the poor benefit from health care and receive a basic package is a widely shared policy objective (World Bank, 2004). Empirical evidence that shows high income elasticities for health care, and thus large inequalities between poor and rich, but rather low price elasticities that tend to be larger for the poor (Jimenez, 1995; Gertler and Hammer, 1997). Targeted prices subsidies for medical care are therefore often advocated as means to increase access to medical care for the poor, as demand side subsidies for medical care are often argued to be more effective in reaching the poor than supply side interventions. However, there is little direct empirical evidence on the merits of this recommendation.

The health care component of the Indonesian Social Safety Net programme, initiated to protect the poor from the effects of the economic crisis that hit the country in 1997, is a very particular kind of health care intervention, which included both a targeted price subsidy and a public spending component. Households that were thought to be most vulnerable to economic shocks were allocated health cards, which entitled all household members to the price subsidy. Health care facilities that provided the subsidised care received extra budgetary support to compensate for the increased demand.

There are some distinct features to the JPS health programme. First, the price subsidy only applied to public service providers. Private sector health care providers were not included in the scheme. Second, targeting and allocation of the budgetary support to health care providers was decentralised to district committees. However, the transfers were made directly from Jakarta to the public health care facilities, through specially created accounts at the post office. Third, there was a loose relationship between the utilisation of the health card and the compensation that the health care providers received in return. Compensation was allocated to districts based on the estimated number of households eligible for the health card programme and not based on actual utilisation of the health cards.

This chapter focuses on the effect of the Indonesian health card programme on demand for primary outpatient health care. The particular design allows us to investigate a number of interesting questions.

First, it provides the opportunity of an *ex post* evaluation of a targeted price subsidy for health care which was implemented on a national scale. Most studies that discuss the effectiveness of health policy draw on simulation based health care demand models, which make *ex ante* predictions of possible policy scenario's given some estimated parameters. The drawback of these simulations is that the underlying estimates are often based on cross sectional data which typically show little (spatial) variation. In effect, these simulations often concern out of sample prediction where the forecasted interventions lie outside the range of the observed price data (Gertler and Hammer, 1997). Although ex post studies do not suffer from this problem, there is relatively little empirical work that evaluates actual pricing policies in health care. Moreover, only few of these studies take account of the endogenous nature of public interventions in their estimation strategy.[1] This chapter aims to contribute to that literature.

Second, since the health card only entitled the user to free services at public providers we can directly investigate substitution effects between private and public providers. This is difficult in health care demand studies, as information on the price menu offered by

[1]Using data from a randomised health insurance and cost sharing experiment in the United States, Manning *et al.* (1987) estimate the demand for outpatient care. Gertler and Molyneaux (1997) use panel data to evaluate an experiment of a user fee increase for outpatient services in Indonesia. Regarding targeted health care subsidies, the Medicaid programme in the US is probably the most studied. Currie and Gruber (1996) and Currie and Thomas (1995) exploit variation in legislature across states to control for endogeneity of the programme. In an analysis of a school based health insurance scheme in Egypt, Yip and Berman (2001) treat participation as selection on observables.

alternative health care providers is often not available. As an alternative to exogenous price data many models estimate the demand for medical care based on proxy variables derived from (endogenous) household expenditure data[2] or variation in indirect cost measures, such as opportunity costs due to loss of work or travel time to the nearest provider.[3] However, opportunity costs do not vary by public or private provider and the same will often hold for travel time. For instance, doctors working at public providers in Indonesia also often maintain private practices making it impossible to use travel time variation to estimate substitution effects. Studies that do manage to identify price variation across provider types generally find substantial substitution effects between public and private providers as a result of public price policy.[4]

The third contribution of this chapter is that we compare the effect of a targeted price subsidy with that of increased public health care spending. Existing empirical evidence is inconclusive regarding causality between spending and health outcomes (World Bank, 2004; Filmer and Pritchett, 1999). In the health care demand literature policy scenarios such as reinvesting funds (from raising user fees, for example) into the public health sector are often discussed and simulated. While appealing for policy, this requires strong assumptions about the supply response of health care providers (such as the cost structure and the performance of the government or local authorities). In case of the JPS intervention we directly observe effect of increased public spending without making these assumptions. There are empirical studies that use actual provider or community data to show that an increase in supply and quality of care, and especially drug availability at health facilities, has a significant effect on utilisation.[5] The problem with these quality and supply variables is that they are often endogenous due to government policy, and that the measured effects are likely to capture both supply and demand effects. While some studies manage to control for the former problem, it is much harder to control for the latter.

In this chapter we make an attempt to disentangle the health card effect and the effect of the budgetary support on utilisation. Given the weak link between the health card programme and the compensation to health care providers, our approach will be to treat these two components of the programme as two separate interventions. We will

[2] E.g. Gertler, Locay and Sanderson (1987), Lavy and Quigley (1993), Ching (1995), Mocan, Tekin and Zax (2000).

[3] E.g., Gertler and van der Gaag (1990), Dow (1999).

[4] E.g., Mwabu, Ainsworth and Nyamete (1993); Sahn, Younger and Genicot (2003).

[5] Lavy and Quigley (1993) define quality as the type of provider for a study in Ghana; Lavy and Germain (1994) find strong effects of supply of drugs, staff and services; Mwabu *et al.* (1993), Akin, Guilkey and Denton (1995), and Akin *et al.* (1998) use facility level data and find large effects of drug availability; Sahn *et al.* (2003) use community level data to find similarly strong effects of availability of drug and medical staff.

argue that the transfers made to the public sector providers benefited all potential users while the price subsidy was only available to those who received a health card. We make an attempt to disentangle the two effects. Our results suggest that the largest share of the programme's effect is due to increased public spending.

Finally, we evaluate the distribution of the effects of both the demand and supply side interventions. The literature suggests that the poor are more sensitive to price effects than the rich.[6] But even if households receive their health cards, there may still be barriers to using these benefits, such as lack of information, regional shortage of providers, or opportunity costs unabridged by the health card. Such barriers are likely to vary by population sub-group, households or even individual characteristics (Blank and Card, 1991; Currie and Thomas, 1995) and are likely to be higher for the poor. Alternatively, health card recipients may be reluctant to utilise their benefits simply because of a preconception that subsidised care is of inferior quality to non-subsidised health care (Arhin, 1994). Evidence of such barriers to using the health card has been discussed at length in chapter 3, showing that under-usage of the health cards is indeed higher for the poor than for the non-poor. Given the loose relationship between JPS budgetary support and the actual use of health cards, it may also be that health care facilities are reluctant to provide free services, or at least service of similar quality as provided to non-subsidised patients. In this case the non-poor are likely to capture a large part of the benefits from extra public health care spending.

The results in this chapter show the effects of the price subsidy and supply impulse to differ by income group. For low-income groups (with relatively high price elasticity) we find both a substitution from public to private care and an increase in total utilisation due to the health card, but little effect from increased spending. However, for the more wealthy groups (less sensitive to price changes) we find the substitution effect to be more dominant and the supply-induced effect of the budget increase to be larger, possibly since the rich typically face less barriers to access to medical care than the poor. Overall, the non-poor captured most of the benefit, despite pro-poor targeting of the health cards. The weak link between financing and utilisation of health cards resulted in that most programme benefits were captured by the rich.

The organisation of the chapter is as follows. The next section gives an overview of the data. Section 6.3 focuses on the evaluation problem and sets out the strategy for disentangling and estimating the impact of both the health card and the supply impulse on utilisation of outpatient care. Section 6.4 highlights some caveats and examines the

[6] E.g., Gertler *et al.* (1987), Manning *et al.* (1987), Sauerborn, Nougtara and Latimer (1994), Ching (1995), Yip and Berman (2001), Sahn *et al.* (2003).

sensitivity of the results to the main assumptions of the study. Section 6.5 concludes.

6.2 The data

This study draws on Indonesia's nation-wide socioeconomic household survey (*Susenas*). The 1999 JPS module provides information on household participation in the health card programme. The survey was fielded in February 1999, while the health card programme started in the fall of 1998. The results of this analysis therefore reflect the experience of the first months of operation of the programme. For this reason, and data limitations, we limit the analysis to the impact of the programme on the access to medical care (in terms of utilisation), and do not endeavour to estimate the effect on health. Health effects are likely to take longer to materialise. The JPS module sampled 202,089 households and collected a wide range of socioeconomic indicators along with a measure of consumption. In the area of health, the survey collected information on self-reported illness, utilisation of medical services, user fees and ownership and utilisation of the health card. We also use the 1998 Susenas as this provides the pre-intervention data needed for the analysis. This round is also fielded in February, includes 207,645 households and covers the same questionnaire and variables as the 1999 survey, except for the JPS programmes.

The 1996 village level census, *Podes*, provides pre-intervention information on accessibility and supply of health services, and various other community characteristics. The 1996 Podes includes 66,486 villages (*desa*) and townships (*kelurahan*) and can be merged with the Susenas.

Besides the micro data we also use administrative data concerning the 1998/1999 budget for the Social Safety Net programme. This data includes the budget allocated to 293 districts (*kabupaten*) to implement the health card programme and to compensate the public health clinics (*Puskesmas*) and village midwives (*Bidan di desa*) for the expected extra demand for health services resulting from the health card programme. The largest share of this budget was directly transferred to public health care providers. The transfers were made in two to four phases, depending on the province, starting in the last quarter of 1998. By the time of the survey JPS budgets had arrived at the health centres.

6.3 Impact of the Health Card Programme on Utilisation

6.3.1 Utilisation of medical services and the health card programme

The trend in health care utilisation has already been described in chapter 2. For the analysis in this chapter it suffices to recall the decline in health care utilisation that was observed in 1998. Utilisation of public care suffered the most during the crisis. The blame for the bad performance of the public sector has been placed with budget cuts and rising costs of drugs and medical supplies, which has lead to a strong decline in quality and supply of care. However, in 1999 the public sector saw a revival. This chapter will investigate to what extent the JPS health programme has been responsible for this revival.

By February 1999 the health card programme was already of a substantial magnitude with 10.6 percent of Indonesians reporting that their household was allocated a health card (see chapter 3). For the poor this percentage is even higher: 32 percent of the people from the two poorest quintiles lived in a household that was allocated a health card. So even though we are analysing the programme in its very early stages, it was already in full swing at the time of the 1999 Susenas survey.

6.3.2 Disentangling effects of two interventions

What would have been the utilisation of outpatient health services if the SSN health card programme had not existed? This question comprises two effects: the effect of the health card price subsidy and the effect of the additional budgetary resources made available to public sector services trough the SSN programme. By virtue of the weak link between these two components of the programme, our approach will be to treat the two effects as two separate interventions.

The maintained assumption is that the first intervention – the distribution of health cards – accrues benefits only to those who actually own a health card, while the second intervention can potentially benefit the whole population, depending on the size of the grant to the health care provider. This assumption rules out external or general equilibrium effects. Because we are dealing with short term impacts, we will assume that health related general equilibrium effects are not substantial since they are likely to take longer to materialise. However, externalities through congestion or crowding out induced by the programme may also compromise the independence assumption. We will investigate the sensitivity to this assumption later in the chapter.

Under the independence assumption, the combined average impact of the two interventions can be written as the sum of the two impacts separately. Let $Y_i(h_i, q_j)$ denote the outcome for individual i, living in district j, as a function of the two interventions. If a person lives in a household that has received a health card then $h_i = 1$, while $h_i = 0$ for non-recipients. q_j reflects the JPS budgetary support to public health care providers in the area where the person lives (indicated by JPS_j).

We want to know to what extent the observed development in utilisation from 1998 to 1999 is due to these two interventions. The overall impact of the programme that we want to retrieve can be expressed as a weighted mean of the impact on the population with a health card ($h_i = 1, q_j = JPS_j$) and people who did not receive a health card, but only benefited from the budget increase ($h_i = 0, q_j = JPS_j$). Assuming that utilisation of health card owners and that of non-health card owners is independent, we can write the overall impact as

$$\begin{aligned} pE\left[Y_i(1, JPS_j) - Y_i(0,0) \mid h_i = 1, q_j = JPS_j\right] \\ +(1-p)\, E\left[Y_i(0, JPS_j) - Y_i(0,0) \mid h_i = 0, q_j = JPS_j\right] \end{aligned} \tag{6.1}$$

where $p = P(h_i = 1)$ is the probability of receiving a health card. The observed average outcome for the population with a health card is given by $E[Y_i(1, JPS_j) \mid h_i = 1, q_j = JPS_j]$, while $E[Y_i(0, JPS_j) \mid h_i = 0, q_j = JPS_j]$ reflects the observed average outcome for individuals who did not receive a health card. The counterfactual, $Y_i(0,0)$, is the outcome in the event that the Social Safety Net had not been implemented. By adding and subtracting $pE[Y_i(0, JPS_j) \mid h_i = 1, q_j = JPS_j]$, we can rewrite equation (6.1) as

$$\begin{aligned} & pE\left[Y_i(1, JPS_j) - Y_i(0, JPS_j) \mid h_i = 1, q_j = JPS_j\right] \\ & +E\left[Y_i(0, JPS_j) - Y_i(0,0) \mid q_j = JPS_j\right] \end{aligned} \tag{6.2}$$

Here the first term (weighted by p) gives the impact of the pure health card programme conditional on the budget increase, for those who own a health card. We will refer to this as the *direct* effect of the programme. The second term reflects the effect of budget increase for the whole population, which we will refer to as the *indirect* effect of the JPS programme.

6.3.3 Estimation strategy

We will estimate both the direct health card effect and the overall effect. We cannot directly identify the indirect effect of the programme. Instead, we derive the impact of the general increase in funding to public services by subtracting the direct effect estimate from the total effect estimate.

First, we concentrate on the estimation of the direct effect of the health card intervention. Since both health card and non-health card owners benefited from the transfer of funds to health care providers, this measures the differential effect of owning a health card conditional on the transfer programme. For obvious reasons, a direct comparison between health card owners and non-health card owners after the introduction of the programme does not yield a valid impact estimate. The expressions above are conditional upon selection and since selection was not random, we cannot presume that $E[Y_i(0, JPS_j) \mid h_i = 1, q_j = JPS_j] = E[Y_i(0, JPS_j) \mid h_i = 0, q_j = JPS_j]$. The health card was distributed to poor households, and even without a health card their utilisation would have been different from the relatively wealthier non-health card households. It is also possible that the health cards may have been allocated based on needs. In that case health card recipients would, on average, use more health care, even without the health card.

There are various approaches one can take to correct for this non-random placement of the programme (e.g., Heckman, LaLonde and Smith, 1999). A frequently used method is propensity score matching, which relies on matching on observables, and the assumption of conditional independence.[7] That is, conditional on a set of observed characteristics selection into the programme can be treated as random (Heckman and Robb, 1985; Holland, 1986). Recent advances have greatly increased the popularity of this method.[8] The success in reducing the systematic differences between the control and treatment group increases when more variables are used to match households. However, the more variables are used, the more difficult it will become to match households. Rosenbaum and Rubin (1983) proved that if it is valid to match on all of the selected variables separately, it is equally valid to match on the propensity score only. The propensity score is the probability of obtaining treatment as a function of the observed matching variables. This result

[7] We experimented with instrumental variables but abandoned this approach because we are not convinced that we are able to construct adequate instruments. We used variables that measure the perception of fairness of the distribution of health cards in the district. But the results were very sensitive to specification and choice of instrument. We also experimented with 1997 district BKKBN estimates. However, using 1998 data we found that these variables appear to be correlated with the level of utilisation (but not with changes).

[8] See Imbens (2003) for a survey. Smith and Todd (2005) provide an insightful discussion on the application and pitfalls of propensity score matching in the recent literature.

greatly reduces the dimensionality of the problem. Instead of having to match on several variables, it now suffices to condition on just one variable, the propensity score. The propensity score function can be estimated with a logit model. The unit of our analysis is the household, as health cards were distributed at this level. Households in the treatment group are matched to households in the potential control group. Note that as a result, the sample size of the treatment and matched control group – in terms of individuals – are different as the household sizes vary.

The main weakness of this method is that one cannot be sure that all systematic differences between the control and treatment group that influence utilisation have been removed during the match. The extent in which the propensity score matching will reduce the bias depends on the specification of the propensity score model and the quality of the control variables (Heckman, Ichimura and Todd, 1997; Heckman, Ichimura, Smith and Todd, 1998). It is therefore crucial to understand the programme design and to include sufficient information about the selection procedure (at all allocation levels) in the model. There are three sources of bias that we want to deal with. The first is the endogenous placement of health cards with households. Second, since we want to estimate the *direct* health card effect, we want to purge it from any systematic differences in regional programme intensity between the control and treatment group. Finally, we need to take account of increased demand for public services, which may result from the allocation of health cards.

To control for the latter two soures of bias we include district fixed effects. These capture any between district variation in allocation of health cards and JPS funding. BKKBN poverty estimates for sub-districts control for allocation of subsidy within districts and the number of health cards issued in the areas covered by the facilities. Thus, we are matching households who live in areas that enjoy/suffer similar programme intensity (in terms of health card coverage and JPS budget) and similar supply shocks in health care.

Endogenous programme placement is caused by purposive targeting at different stages in the decentralised allocation process. To control for endogenous programme placement at the village level we include variables from the Podes that reflect pre-programme access to health care. These include the number of public health clinics, auxiliary health clinics and maternity facilities in the village, dummy variables indicating whether the majority of village traffic is by land, and a dummy variable reflecting the village leaders' opinion about the accessibility of health clinics. As local facility staff distributes the health cards, we include the number of doctors and village midwives living in the village (per 1000 inhabitants) as a proxy for informal contacts within the village. Finally, the level of education of the village leader is included, as well as dummy variables indicating IDT eligibility and whether the village is located in a rural area.

For households we include the five BKKBN allocation criteria as dummy variables. Other household welfare variables refer to housing characteristics (status of house occupied, type of roof, walls and floor, sewage, sanitation and drinking water facilities, and source of light), sector of main source of household income, and employment status of the head of household. We further control for household composition (gender and age), household size and head of household characteristics (gender and education level). Per capita consumption is endogenous since a health card reduces health care expenses, and is therefore omitted. A household with a health card would, on average, report a lower consumption level than it would if it had not received a health card. If we add household expenditure to the propensity score function we would be constructing a control group that is less wealthy than the intervention group.[9] Consequently, we would overestimate the health card effect.

Health status is the one important unobserved variable that is missing from this specification. Soelaksono *et al.* (1999) provide some evidence that health cards were allocated based on illness. This is further reinforced by the fact that self-reported illness is higher amongst health card owners. This would actually suggest that the positive bias due to health status outweighs the negative bias due to pro-poor targeting. The Susenas records self-reported illness, but this is typically prone to reporting bias, and may be endogenous to health card allocation.[10] We therefore omit health status from the propensity score function. Many of the individual characteristics will reduce the health bias (e.g. age, housing and sanitary conditions, BKKBN criteria) but we acknowledge that some may remain. However, later in the paper we will show that the potential bias from omitting health status is small, and that the estimation results are robust and within reasonable bounds.

We estimated the propensity score function separately for five main regions in Indonesia.[11] In this way we restricted the match to households living in the same region. A household with a health card living in Java could for instance, never be matched with a household without a health card living in Sumatra. The reason for doing so is that

[9]See van de Walle (2003) for a discussion on assumptions about behavioural responses regarding the effect of public policy on household consumption.

[10]Using an experiment with user fee increases in Indonesia, Dow *et al.* (2000) provide a nice illustration of the problem of reporting bias and measurement error in self reported health status. Whereas objective measures of health show that increasing user fees leads to a deterioration of health status, self reported measures suggest an improvement in health. They argue that this reporting bias is correlated with exposure to the health system, which is affected by the user fee increase. See also Strauss and Thomas (1998) for a more general discussion.

[11]The 5 regions we define are (i) Java and Bali, (ii) Sumatra, (iii) Sulawesi, (iv) Kalimantan and (v) Other Islands.

we believe that there are unobserved characteristics which vary by region that influence the effect that other variables have on the probability of receiving a health card.[12] The Pseudo R-squared for the regional models ranged from 0.12 to 0.26.[13]

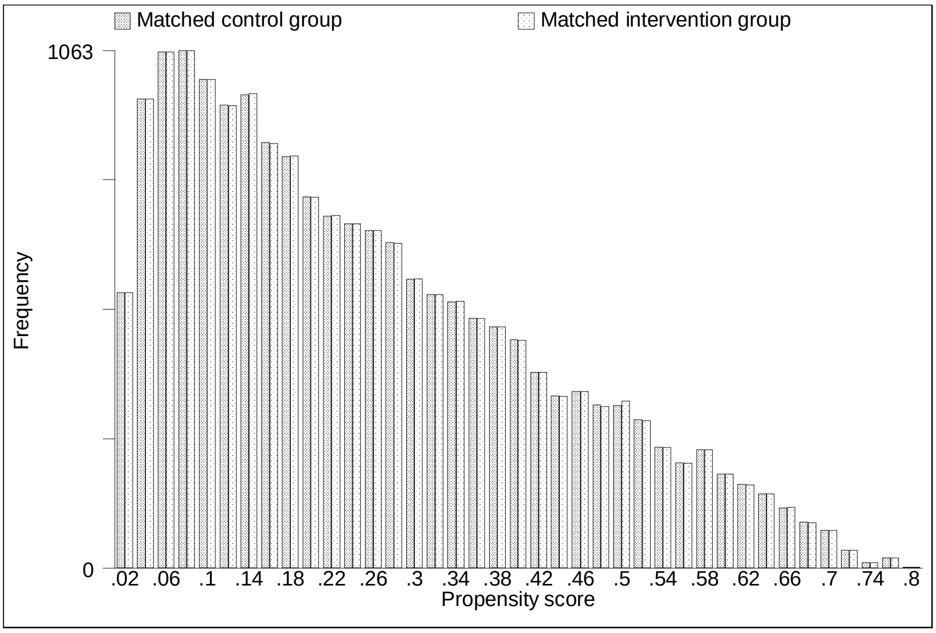

Figure 6.1: Histogram of the propensity score for matched households (bin size = 0.02)

Households that own a health card are matched to households without a health card, based on the estimated propensity score. There is a variety of matching methods that can be applied (Dehejia and Wahba, 1999 and 2002; Imbens, 2003). We implemented nearest neighbour matching, the simplest matching procedure. For each household in the treatment group we selected a control-household with the nearest value of the propensity score. This way of constructing a control group basically boils down to re-weighing the potential control group. Those households that are not matched receive a weight of zero, those who are matched once receive a weight of one, and those matched more than once receive a weight higher than one. The choice between allowing matching with replacement or without involves the trade-off between increasing precision and reducing the bias. Matching with replacement will give the least biased estimate, but reduces precision of the estimate, as the weights for multiple matched observations increase the variance. The drawback of matching without replacement is that it yields a shortage of possible matches for those households with a high propensity score. We used the rule

[12]See, for example, Smith and Todd (2005), Heckman, Ichimura and Todd (1997), and Heckman, Ichimura, Smith and Todd (1998), who raise concern about the potential bias due to "geographic mismatch" in the matching process.

[13]See table 6.9 in appendix 6.A for the propensity score function estimation results.

that when the match obtained without replacement had a propensity score that differed more than 0.001 from the propensity score of the household in the treatment group, we resorted to matching with replacement. If no match was found within a radius of 0.001 we did not match the household to a control.

The quality of match is best illustrated using a graph. Figure 6.1 graphs the distribution of the propensity score for the matched households in a histogram, while table 6.1 depicts the distribution of the propensity score for the intervention group, potential controls and households matched more than once. The number of matched household's decreases as the probability of selection increases. The region of overlapping support ranges from 0.0008 to 0.8473. Households outside this range are not considered in the matching procedure.

Table 6.1: Distribution of propensity score for all households and for the matched pairs

Propensity score	All households		Matched pairs		Nr. of households in control group matched more than once
	No health card	Health card	No health card	Health card	
0.0 - 0.1	128,128	4,658	4,658	4,658	0
0.1 - 0.2	26,544	4,405	4,406	4,405	0
0.2 - 0.3	10,003	3,388	3,386	3,387	3
0.3 - 0.4	4,828	2,605	2,589	2,588	21
0.4 - 0.5	2,318	1,839	1,788	1,794	68
0.5 - 0.6	1,105	1,238	1,208	1,203	161
0.6 - 0.7	378	664	620	620	137
0.7 - 0.8	57	177	72	72	16
0.8 - 0.9	5	19	0	0	0
Total	173,366	18,993	18,727	18,727	406

Note: Range of common support: [0.0008, 0.8473].

Table 6.2 provides descriptive statistics for health card owners and others. Column 2 shows the statistics for households without a health card, while column 3 shows the characteristics for households that did receive a health card. It appears that, before the match, households that own a health card perform worse on the BKKBN criteria, slightly larger and work more often in agriculture compared to non-health card owners. Heads of households with a health card have on average a lower education and are more likely to be females.

The matched households are very similar on the basis of the individual observed characteristics, which entered into the matching function. Columns 4 and 5 in table 6.2 present the descriptive statistics for the matched samples, and columns 6 and 7 show the difference in means of the covariates. The top panel presents variables that were included in the matching function, and shows that the two samples are well balanced across the observed characteristics.

The second panel shows that the district dummy variables managed to control for the supply shock in the matching process. Both programme intensity variables are balanced for the matched households, while they differ strongly for the non-matched households. This confirms that the district dummy variables in the matching function managed to control for variation in the size of the grants and health cards coverage in the district. The matching has also balanced the weight for age Z score (WAZ) of children under 5.[14] Weight is indicative for the health children over a period of time of which, in this case, will mostly reflect the period before the launch of the health card. It is thus – in the absence of panel data – our best proxy for balance in pre-intervention outcome variables.[15] In section 6.4 we will further investigate the robustness of the impact estimate to health status.

The differential impact of ownership of a health card is estimated by comparing utilisation patterns of the treatment and matched control group. Comparing means yields the average impact of the direct health card intervention on health card owners. It can easily be obtained by estimating the regression

$$Y_i = c + \beta h_i + \varepsilon_i \tag{6.3}$$

on the matched sample applying sample weights, where c is a constant and ε_i an i.i.d error term. $\hat{\beta}$ is an unbiased estimate of the treatment effect for those who are selected into the programme, i.e.

$$\hat{\beta} = E\left[Y_i\left(1, JPS_j\right) - Y_i\left(0, JPS_j\right) \mid h_i = 1, q_j = JPS_j\right] \tag{6.4}$$

Weighting this by the estimated probability of selection into the programme, $\hat{p} = P(h_i = 1)$, gives us the average *direct* health card effect, $\hat{p}\hat{\beta}$, defined in equation (6.2).

[14]The WAZ score is based on a 1999 Susenas nutrition module, covering 72,848 children under 5.

[15]Waters *et al.* (2003) find that the crisis had no observable effect on the WAZ score. Effects of the health card programme on the WAZ are unlikely as this did not cover nutritional programmes.

Table 6.2: Descriptive statistics for households with and without a health card, and for matched pairs

	All households		Matched pairs			
Variables	No health card	Health card	No health card [1]	Health card	Diff.	[s.e]
Propensity score	0.0823	0.2488	0.2433	0.2433	-0.0000	0.0018
Female head of household	0.1268	0.1608	0.1618	0.1601	-0.0017	0.0038
Education head of household						
No education completed	0.3641	0.5087	0.5090	0.5073	-0.0017	0.0052
Primary	0.2985	0.3324	0.3289	0.3327	0.0038	0.0049
Junior secondary	0.1220	0.0814	0.0818	0.0818	0.0000	0.0028
Senior secondary	0.1689	0.0667	0.0693	0.0674	-0.0019	0.0026
Higher	0.0465	0.0107	0.0111	0.0108	-0.0003	0.0011
Head of household unemployed	0.0079	0.0074	0.0075	0.0074	-0.0001	0.0009
Household size	4.2043	4.2576	4.2211	4.2449	0.0238	0.0189
BKKBN criteria						
Worship	0.9343	0.8894	0.8911	0.8902	-0.0010	0.0032
Food	0.9835	0.9778	0.9785	0.9790	0.0004	0.0015
Clothing	0.9645	0.9473	0.9487	0.9487	0.0000	0.0023
Floor	0.8193	0.5935	0.5962	0.5954	-0.0008	0.0051
Health	0.8899	0.9061	0.9056	0.9057	0.0001	0.0030
Main source of household income						
Agriculture, farming	0.4551	0.5568	0.5526	0.5546	0.0020	0.0051
Mining, quarrying	0.0097	0.0089	0.0089	0.0089	-0.0001	0.0010
Processing industry	0.0687	0.0685	0.0655	0.0682	0.0027	0.0026

Continued on next page...

... table 6.2 continued

	All households		Matched pairs			
Variables	No health card	Health card	No health card [1]	Health card	Diff.	[s.e]
Electricity, gas, water	0.0022	0.0007	0.0009	0.0007	-0.0002	0.0003
Construction	0.0400	0.0494	0.0507	0.0496	-0.0011	0.0023
Trade	0.1482	0.1180	0.1206	0.1193	-0.0013	0.0034
Transport., storage, comm.	0.0510	0.0519	0.0522	0.0521	-0.0002	0.0023
Finance, insurance, real estate	0.0091	0.0031	0.0026	0.0031	0.0005	0.0006
Services	0.1462	0.0931	0.0957	0.0936	-0.0021	0.0030
Other	0.0028	0.0037	0.0033	0.0036	0.0004	0.0006
Income recipient	0.0672	0.0459	0.0470	0.0464	-0.0006	0.0022
Rural area	0.6792	0.7880	0.7856	0.7862	0.0006	0.0042
IDT village	0.2822	0.3495	0.3476	0.3444	-0.0032	0.0049
BKKBN rate per sub-district	0.3088	0.4407	0.4417	0.4390	-0.0028	0.0026
Program intensity at district level						
JPS budget per capita	1.6164	1.8178	1.8154	1.8147	-0.0007	0.0099
Health card coverage	0.0886	0.1885	0.1865	0.1870	0.0004	0.0012
Member of household ill	0.3110	0.3620	0.3293	0.3605	0.0312	0.0049
Weight for Age Z-score, children under 5 [2]	-1.2116	-1.2943	-1.2924	-1.2987	-0.0063	0.0244
Number of observations	173,366	18,993	18,727	18,727		

[1] Includes 406 households that are matched more than once.

[2] Susenas nutrition module, 1999. Total sample is 7,902 (health card) and 64,946 (no health card) children. The matched sample contains 7,502 (health card) and 6,891 (no health card) children.

The overall impact of the programme (equation (6.1)) is obtained by exploiting regional variation in the financial compensation for the health card programme to public health care providers, and the fact that the allocation to districts was based on pre-intervention poverty estimates. We analyse the utilisation rates before the introduction of the health card programme – based on the 1998 Susenas – and compare these with the situation right after the introduction of the health card programme. The resulting impact estimate is a result of the two interventions acting simultaneously. Later in the chapter we evaluate the robustness of this approach. To measure the variation in JPS compensation we use administrative data concerning the 1998/1999 budget that was allocated for transfers to public health facilities. The variation was substantial. For example, we found that the amount of compensation, weighted by the district population size, in Sulawesi is 29 percent higher than in Sumatra and 34 percent higher that in Java/Bali, but about half of what is allocated to the smaller islands (table 6.3).

Table 6.3: JPS budget allocation to public health care providers, 1998/1999 (1000' Rupiah)

Region	Total budget *Puskesmas* and village midwife*	Population size†	Budget per capita	Health card coverage	Number of districts
Java and Bali	158,524,734	123,646,893	1.282	0.139	117
Sumatra	57,686,076	43,396,301	1.329	0.072	73
Sulawesi	25,009,892	14,553,660	1.718	0.049	40
Kalimantan	15,747,384	11,210,671	1.405	0.052	29
Other islands	36,024,406	11,860,142	3.037	0.085	34
Indonesia	292,992,492	204,667,667	1.432	0.106	293

Source: * Ministry of Health and Social Welfare, Indonesia, † Susenas.

We model the effect of the general increase in funding as a linear function of the budget allocation. For district j, in time period t, the utilisation of health services is written as

$$Y_{jt} = \alpha_j + \gamma \frac{JPS_{jt}}{N_{jt}} + \phi' W_{jt} + \theta_0 d_t + \sum_{r=2}^{5} \theta_r d_r d_t + \varepsilon_{jt} \tag{6.5}$$

where JPS_j is the amount of compensation for public health clinics allocated to district j, N_j denotes the district population size. Subscript t indicates time and refers to either the time period before the intervention (1998) or the time period after the intervention (1999). We include a time dummy variable, taking value $d_t = 0$ if $t = 1998$ or $d_t = 1$ if $t = 1999$. The time variable has been interacted with 5 region specific fixed effects, d_r, in order to allow for some flexibility in capturing the time effect.[16] In the pre-intervention year JPS_j equals zero for all districts. We also add a set of regional welfare and demographic characteristics, W_{jt}, to the model. These include the poverty profile of the districts[17], the average age and household size, the district population size, and the fraction of the population living in a rural area. Frankenberg, Smith and Thomas (2003) show evidence of changes in household size, migration between urban and rural areas due to households restructuring their composition in response to the crisis. While the average household size increased in (lower cost) rural areas, the number of working age family members increased in urban households.

The non-random allocation of the JPS budget is accounted for by a district fixed effect, α_j. This removes any bias due to unobserved time invariant factors that affect geographic allocation and are also correlated with health care utilisation. The fact that the JPS budget allocation was determined by static pre-programme poverty estimates, the BKKBN classification, and not on the basis of dynamic changes in poverty legitimises the fixed effects approach.

Taking differences across districts over time gives

$$\Delta Y_{jt} = \gamma \frac{JPS_{jt}}{N_{jt}} + \phi' \Delta W_{jt} + \theta_0 + \sum_{r=2}^{5} \theta_r d_r + \Delta \varepsilon_{jt} \tag{6.6}$$

Estimating (6.5) by OLS yields unbiased estimates under the assumption that the allocation of JPS funds is not correlated with time variant unobservables. If the geographic allocation is correlated with important district-level trends that are not captured by the time dummies or ΔW_{jt}, then OLS estimates may still be biased. This is not very likely, given that the BKKBN indices are badly suited for capturing the changes in welfare. Further reassurance is given by the fact that we find no correlation between JPS allocation (per capita) and changes in utilisation from 1997 to 1998.[18]

The overall impact of the programme is then obtained by taking a population weighted average of the effects for the districts

$$\sum_{j=1}^{J} \hat{\gamma} \frac{JPS_j}{N_j} \frac{N_j}{N} = \hat{\gamma} \overline{JPS}_j \tag{6.7}$$

[16] Java and Bali (region 1) are used as reference group.

[17] The poverty profile is portrayed by the poverty rate (P_0) and poverty gap (P_1), based on the expenditure data from Susenas. As in chapter 5, the povertylines are set such that the average head count for Indonesia is 24.1% in February 1998 and 27.1% in February 1999 (Suryahadi, Sumarto and Pritchett, 2003).

[18] See table 6.10 in appendix 6.A.

where $\overline{JPS}_j$ is the average financial compensation for the health card programme per person across the country, and J the number of districts.

The estimated impact of the supply impulse on the utilisation of outpatient services (i.e., the indirect effect) is given by the difference between the estimate of the average total effect and the average direct health card. Inserting (6.7) and the estimate of the direct effect, (6.4), into (6.2) yields an expression for the impact of the general budget increase for public service providers

$$\hat{\gamma}\overline{JPS}_j - \hat{p}\hat{\beta} = E\left[Y_i\left(0, JPS_j\right) - Y_i\left(0, 0\right) \mid q_j = JPS_j\right] \tag{6.8}$$

6.3.4 Results

The estimation results of the direct health card effect on outpatient utilisation for health card owners ($\hat{\beta}$) and the average direct effect ($\hat{p}\hat{\beta}$), are given in table 6.4. The estimate of $\hat{p}$ is simply the fraction of individuals living in a household that owns a health card. The table also shows contact rates for outpatient services for the matched intervention and control groups, and the percentage change relative to the counterfactual. The effects are estimated for reported utilisation over a one-month reference period.[19]

Health card ownership resulted in a 1 percentage point increase in the use of outpatient services, which is a 9.1 percent increase relative to the base counterfactual. This increase was due to an increase in utilisation from the poorest four quintiles, while for the richer quintile we only observe a substitution effect from private to public health care providers. The highest increase, relative to the base, is seen for the third quintile (16.8 percent), followed by the poorest group (14.2). For all income groups health card ownership resulted in an increase in the use of public sector services and a decrease in the use of private sector services. For the richest quintile the two effects cancelled out, as we see a small, statistically not significant, increase in overall utilisation. The shift from private to public care seems to have occurred in both urban and rural areas. The health card programme affected utilisation amongst women more than it did amongst men, possibly because of the maternity services covered under the health card programme. Both the overall increase in outpatient visits and the substitution effect from private to public were larger for women.

[19] Each year the Core of the Susenas collects utilisation using a one-month reference period. We also estimated the effects based on a three months reference period, which was used in the 1999 JPS module. However, these data may partly reflect pre-intervention outcomes, so we need to be careful interpreting these results. Nevertheless, the estimates show a similar impact as the one-month recall period. These results are reported in table 6.11 in appendix 6.A.

Table 6.4: Impact of health card on utilisation of outpatient services (direct health card effect, one month reference period)

	Intervention group	Control group	Difference ($\hat{\beta}$)	[s.e.][1]	% Change	Direct effect ($\hat{p}\hat{\beta}$)	$\hat{p}$	Number of observations Intervention	Control
All outpatient care									
Quintile 1 (poor)	0.0993	0.0869	0.0123	[0.0032]**	14.2	0.0023	0.184	25,029	20,411
Quintile 2	0.1206	0.1080	0.0126	[0.0040]**	11.7	0.0017	0.137	19,561	17,905
Quintile 3	0.1333	0.1142	0.0191	[0.0045]**	16.8	0.0020	0.106	15,658	15,426
Quintile 4	0.1453	0.1292	0.0161	[0.0055]**	12.4	0.0011	0.071	10,922	12,048
Quintile 5 (rich)	0.1510	0.1451	0.0059	[0.0079]	4.0	0.0002	0.037	5,642	8,090
Male	0.1158	0.1069	0.0089	[0.0030]**	8.3	0.0009	0.105	38,062	36,641
Female	0.1270	0.1157	0.0113	[0.0029]**	9.8	0.0012	0.107	38,841	37,345
Urban	0.1392	0.1281	0.0110	[0.0051]**	8.6	0.0008	0.073	17,888	16,853
Rural	0.1149	0.1061	0.0088	[0.0021]**	8.3	0.0011	0.128	59,015	57,133
All	0.1215	0.1113	0.0101	[0.0020]**	9.1	0.0011	0.106	76,903	73,986
Public outpatient care									
Quintile 1 (poor)	0.0729	0.0542	0.0187	[0.0026]**	34.6	0.0035	0.184	25,029	20,411
Quintile 2	0.0784	0.0585	0.0200	[0.0032]**	34.1	0.0027	0.137	19,561	17,905
Quintile 3	0.0859	0.0575	0.0284	[0.0033]**	49.3	0.0030	0.106	15,658	15,426
Quintile 4	0.0916	0.0627	0.0289	[0.0043]**	46.1	0.0020	0.071	10,922	12,048
Quintile 5 (rich)	0.0841	0.0590	0.0251	[0.0057]**	42.5	0.0009	0.037	5,642	8,090
Male	0.0734	0.0537	0.0197	[0.0021]**	36.8	0.0021	0.105	38,062	36,641
Female	0.0871	0.0622	0.0249	[0.0022]**	40.1	0.0027	0.107	38,841	37,345
Urban	0.0869	0.0628	0.0241	[0.0034]**	38.3	0.0017	0.073	17,888	16,853
Rural	0.0779	0.0565	0.0214	[0.0017]**	38.0	0.0027	0.128	59,015	57,133
All	0.0804	0.0580	0.0224	[0.0015]**	38.6	0.0024	0.106	76,903	73,986
Private outpatient care									
Quintile 1 (poor)	0.0305	0.0371	-0.0066	[0.0022]**	−17.7	-0.0012	0.184	25,029	20,411
Quintile 2	0.0497	0.0547	-0.0051	[0.0030]*	−9.3	-0.0007	0.137	19,561	17,905
Quintile 3	0.0571	0.0641	-0.0070	[0.0036]**	−11.0	-0.0007	0.106	15,658	15,426
Quintile 4	0.0655	0.0765	-0.0110	[0.0041]**	−14.4	-0.0008	0.071	10,922	12,048
Quintile 5 (rich)	0.0803	0.0983	-0.0179	[0.0068]**	−18.2	-0.0007	0.037	5,642	8,090
Male	0.0501	0.0601	-0.0100	[0.0023]**	−16.6	-0.0010	0.105	38,062	36,641
Female	0.0477	0.0606	-0.0129	[0.0021]**	−21.3	-0.0014	0.107	38,841	37,345
Urban	0.0613	0.0726	-0.0113	[0.0041]**	−15.5	-0.0008	0.073	17,888	16,853
Rural	0.0442	0.0565	-0.0123	[0.0015]**	−21.7	-0.0016	0.128	59,015	57,133
All	0.0489	0.0604	-0.0115	[0.0015]**	−19.0	-0.0012	0.106	76,903	73,986

[1] Bootstrapped standard errors with 500 replications.
Significance levels: † : 10% $*$: 5% $**$: 1%

Table 6.5 presents the estimates of γ from equation (6.6), and the estimates of the overall effect of the programme ($\hat{\gamma}\overline{JPS}_j$), defined in equation (6.7). These estimates are also based on a one-month reference period. The results indicate an absolute increase in the use of outpatient services of 0.5 percentage point, which stems mainly from an increase in the use of public services, as the programme does not seem to affect the private sector. We find that the effect is larger for the wealthier quintiles. For the first and third quintiles the estimates are small and not significant. As with the direct health card effect, the overall effect of the programme on public services is larger for females than for males. The programme had the largest impact on the use of public care in rural areas, while for urban areas the estimates are not precise. Since private care seems unaffected, we find similar results for the overall effect on utilisation.

The indirect effect, which could be attributed to an overall supply or quality impulse as a result of the extra budget support in the public sector, seems to have been a main contributor to the increase in the use of public health care services. Combining the estimates in table 6.5 with those referring to the one month reference period in table 6.4 allows us to investigate what share of the increase in the use of public sector services is due to the indirect effect (as defined in equation (6.8)), and to the direct health card effect. The share of the indirect effect to the total effect is given by

$$1 - \frac{\hat{p}\hat{\beta}}{\hat{\gamma}\overline{JPS}_j}$$

About 80 percent of the overall increase in utilisation is a result of the indirect effect. In the public sector about half of the total increase can be attributed to the indirect effect of the budget increase. The results also suggest that the indirect benefits of the programme increase with income. For the richest quintile only 7 percent of the increased utilisation of public care can be attributed to the health card itself, while for the poor there is less clear evidence of an indirect effect. The indirect effect for the poor is smaller, but based on an imprecise estimate. Finally, the supply impulse had an above average effect in rural areas, emphasising the shortage of resources with rural public health care providers.

So can the revival of the public sector utilisation be attributed to the Social Safety Net Programme? It appears to be. The estimates reported in table 6.5 can be used to estimate the utilisation if the health card programme had not existed. From (6.7) it shows that the impact on overall utilisation is the estimate of γ times the average compensation to health care providers ($\overline{JPS}_j$). The results indicate that health card programme increased outpatient contact rate by 0.55 percentage point and the contact rate at public facilities by 0.47 percentage point. Table 6.6 shows the trend in health care utilisation (copied from

Table 6.5: Overall effect of JPS interventions (1 month reference period)

	Coefficient ($\hat{\gamma}$)	[s.e.]	Overall effect [1] ($\hat{\gamma}\overline{JPS}$)	Number of districts
All outpatient care				
Quintile 1 (poor)	0.0039	[0.0041]	0.0056	290
Quintile 2	0.0073	[0.0038]†	0.0105	293
Quintile 3	0.0012	[0.0029]	0.0017	293
Quintile 4	0.0065	[0.0032]*	0.0093	293
Quintile 5 (rich)	0.0075	[0.0036]*	0.0108	293
Male	0.0037	[0.0022]†	0.0053	293
Female	0.0040	[0.0024]†	0.0058	293
Urban	0.0045	[0.0048]	0.0064	286
Rural	0.0060	[0.0028]*	0.0086	276
All	0.0039	[0.0022]†	0.0055	293
Public outpatient care				
Quintile 1 (poor)	0.0035	[0.0033]	0.0049	290
Quintile 2	0.0080	[0.0033]*	0.0115	293
Quintile 3	−0.0001	[0.0022]	−0.0001	293
Quintile 4	0.0059	[0.0023]*	0.0085	293
Quintile 5 (rich)	0.0094	[0.0023]**	0.0134	293
Male	0.0026	[0.0014]†	0.0037	293
Female	0.0040	[0.0017]*	0.0057	293
Urban	0.0016	[0.0032]	0.0023	286
Rural	0.0053	[0.0020]**	0.0076	276
All	0.0033	[0.0015]*	0.0047	293
Private outpatient care				
Quintile 1 (poor)	0.0020	[0.0025]	0.0028	290
Quintile 2	−0.0002	[0.0018]	−0.0003	293
Quintile 3	0.0016	[0.0017]	0.0023	293
Quintile 4	0.0004	[0.0020]	0.0006	293
Quintile 5 (rich)	−0.0016	[0.0028]	−0.0023	293
Male	0.0012	[0.0014]	0.0017	293
Female	0.0005	[0.0014]	0.0008	293
Urban	0.0031	[0.0031]	0.0045	286
Rural	0.0013	[0.0017]	0.0019	276
All	0.0009	[0.0013]	0.0013	293

Note: Detailed estimation results given in tables 6.12 to 6.14 (appendix 6.A).

[1] $\overline{JPS} = 1.432$ (see table 6.3).

Table 6.6: Observed trend in outpatient contact rate from 1995 to 1999, and the counterfactual if the JPS program had not been implemented

Type of provider	Observed trend with JPS				without JPS
	1995	1997	1998	1999	1999
Public	7.00	6.65	5.03	5.34	4.87
Private	6.48	6.71	6.11	5.80	5.67
Modern	12.83	12.83	10.48	10.53	9.98

table 2.5) together with the counterfactual of what would have been public and private sector utilisation in absence of the health card programme. From 1998 to 1999 the contact rate for public sector services increased from 5.0 to 5.3 percent, while the contact rate for modern health care providers remained stable at 10.5 percent. The estimates suggest that without the health card programme public sector utilisation would have dropped further to 4.9 percent, and the overall contact rate would have dropped to 10.0 percent.

6.4 Caveats and sensitivity analysis

6.4.1 Crowding out, congestion and interaction effects

The main assumption underlying our study is that utilisation of health card owners is independent from that of non-health card households. This implies that the number of health card recipients (i.e. programme intensity) in the region does not affect utilisation of care for non-recipients, and that both groups enjoy similar benefits from JPS budget. However, if health care supply would be inelastic, then distributing health cards could lead to congestion and crowding out. For example, if services are delivered to health card owners according to set standards, resources would be redistributed from non-recipients to health card recipients. In this case the estimated direct effect of the health card will be biased upward. The difference in utilisation would consist of the "true" health card effect and the crowding out effect. Alternatively, externalities can manifest themselves if the direct benefits of the health cards do not follow set standards, but are contingent on the available resources. The quality of care provided to health card owners will then increase with the JPS budget.

One might argue that external effects due to health card allocation are likely to be small. Since health card coverage is 11 percent and concentrated among the poor whose health care demand is typically low, it is unlikely that the programme would seriously strain the capacity of health care facilities. For example, if we double the utilisation of public services for health card owners, this will result in 16 percent more outpatient visits for a typical public health care facility. The district dummy variables included in the matching functions do capture programme intensity and the supply shock induced by the JPS (see table 6.2). Moreover, our estimation method allows for effect heterogeneity due to regional variation in programme intensity, since we simply average the estimated impact for all the households with a health card.

Nevertheless, we can test the presence of externalities by controlling for programme intensity when we estimate the direct effect, and including interaction effects of health card ownership with the average number of health cards distributed in the district and the amount of per capita JPS subsidy. Crowding out or congestion would imply that the interaction effects for programme intensity are statistically significant. If crowding out or congestion effects are important, we would expect those to be stronger in areas where the programme is under funded. These are areas where there are relatively many health cards distributed in comparison with the budget that is received. We can test this by including the amount of JPS subsidy per allocated health card as regressor, and interact this with the health card dummy variable. Statistically significant interaction effects would indicate that general equilibrium and external effects are present.

The results in table 6.7 suggest that the estimated direct effect is not biased due to externalities. Specification (1) gives the initial estimates. Specifications (2) and (3) include the interaction terms, and control for the fraction of the population with a health card and the SSN budget per capita allocated to the districts, the sub-district BKKBN index, and district poverty indicators P0 and P1. It further includes a set of individual and households characteristics, IDT village and rural area dummies, and the availability of health facilities in the village. The interaction effects are not statistically significant for public and overall outpatient care. For private care, we find a small and weakly significant effect only for the SSN subsidy interaction term. This is an interesting finding, because doctors working at public providers in Indonesia often maintain private practices. This could suggest that in districts with relative SSN budget abundance, some doctors have used SSN subsidy to treat health card recipients in their private practice. The impact estimate is robust to different specifications. The point estimate for the direct health card effect on overall utilisation is slightly larger, but still within one standard deviation, while the substitution effect between public and private is also slightly larger.

6.4.2 Selection on health status

A third problem, and potentially more serious, is that we have not taken account of the possibility that households may have been selected based on health status. Those with poor health may have received a health card because of their higher anticipated need while

Table 6.7: Sensitivity direct effect estimate (one month reference period)

	(1) [1]	(2) [2]	(3) [2]	(4) [3]
All outpatient care				
Health card	0.0101	0.0106	0.0114	0.0081
	[0.0020]**	[0.0052]**	[0.0021]**	[0.0020]**
Health card × JPS per capita		0.0034		
		[0.0025]		
Health card × health card coverage		-0.0289		
		[0.0188]		
Health card × JPS per health card			-0.0001	
			[0.0000]	
Public outpatient care				
Health card	0.0224	0.0272	0.0239	0.0201
	[0.0015]**	[0.0038]**	[0.0016]**	[0.0016]**
Health card × JPS per capita		-0.0015		
		[0.0019]		
Health card × health card coverage		-0.0059		
		[0.0137]		
Health card × JPS per health card			-0.0000	
			[0.0000]	
Private outpatient care				
Health card	-0.0115	-0.0140	-0.0109	-0.0117
	[0.0015]**	[0.0038]**	[0.0016]**	[0.0015]**
Health card × JPS per capita		0.0035		
		[0.0019]†		
Health card × health card coverage		-0.0161		
		[0.0140]		
Health card × JPS per health card			-0.0001	
			[0.0001]	
Number of observations	150,889	150,889	150,889	151,219

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

[1] Original estimates from table 6.4.

[2] Probit marginal effects. The sample concerns the same set of individuals from matched households as in table 6.4. Detailed estimation results are given in tables 6.15 to 6.17 (appendix 6.A).

[3] Sensitivity to selection on needs bias. The propensity score function includes a dummy variable that indicates whether a health complaint has disrupted work, school or daily activities of a household member. Bootstrapped standard errors with 500 replications. Detailed estimation results are given in table 6.18 (appendix 6.A).

other – otherwise similar – persons did not receive one. Officially health cards should have been distributed based on BKKBN criteria but health status could well have played a role in the actual distribution. If this is true, not including a measure of health status in the matching function will result in an intervention group with a worse health status than the control group. Poor health will, ceteris paribus, increase the demand for health care. The resulting impact estimate will be larger or equal to the true effect.

The only measure of health status the Susenas collects is self-reported illness. However, including self-reported illness in the matching function would likely have resulted in an underestimate of the true health card effect. The evidence indicates that self-reported illness depends on the affordability of care. We find that the rich report more often ill compared to the poor, which is surely not a result of the rich having a worse health status than the poor. If self-reported illness indeed depends on the affordability of health care, and health care is more affordable for those who own a health card, then matching on self reported illness will result in a control group with worse health status than the intervention group. Better health will, ceteris paribus, decrease the demand for primary health care. Hence our impact estimate would have been an underestimate.

The two impact estimates, obtained without and with including self-reported illness in the matching function, can give us some notion on the extent of the bias. The health card effect should lie between the estimate that does control for self-reported illness (lower bound) and that which does not (upper bound). The results suggest that our estimates and conclusions are not sensitive to systematic differences in health status, since the estimated bounds lie close to each other. We included a dummy variable that indicated whether a health complaint has disrupted work, school or daily activities for any member of the household during the last month in the matching function. Specification (4) in table 6.7 gives the results for a one-month reference period. Comparing it with table 6.4, we see that the estimate for all outpatient care decreases slightly, from 0.0101 to 0.0081. The point estimates are within one standard deviation. This leads to an upper- and lower bound for the direct effect of 0.11 to 0.09 percentage point, respectively. The difference comes from the change in demand for public care. The estimated effect for private care remains unchanged.

6.4.3 Total effect

Is the combined effect of the JPS funding and the allocation of health cards, as we defined it in equation (6.1), identified if general equilibrium effects compromise the independence assumption? It could be, for example, that the indirect effect of the subsidy decreases if health card allocation is relatively high. Alternatively, there could be districts with a high JPS allocation but with a delay in health card distribution at the time of the survey. Does the variation in JPS budget then adequately capture the total effect, and does this allow clear interpretation of the indirect effect? To investigate this we added health card coverage to the model, as well as an interaction term with the JPS variable. If the budget allocation does not identify the total effect, we expect the results to be sensitive to the new variables.

Table 6.8: Sensitivity total effect estimate (IV)

	(1) [1]		(2)		(3)	
	coef.	[s.e.]	coef.	[s.e.]	coef.	[s.e.]
All outpatient care						
JPS per capita	0.0039†	[0.0022]	0.0042	[0.0028]	0.0044	[0.0032]
Health card coverage			-0.0118	[0.0628]		
JPS $\times$ health card coverage					-0.0054	[0.0244]
Public outpatient care						
JPS per capita	0.0033*	[0.0015]	0.0037	[0.0019]	0.0039	[0.0022]
Health card coverage			-0.0159	[0.0421]		
JPS $\times$ health card coverage					-0.0060	[0.0163]
Private outpatient care						
JPS per capita	0.0009	[0.0013]	0.0007	[0.0017]	0.0007	[0.0020]
Health card coverage			0.0081	[0.0381]		
JPS $\times$ health card coverage					0.0020	[0.0148]
Instrumented [2]			Health card coverage		JPS $\times$ health card coverage	

Standard errors in brackets.

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

[1] Original estimates from table 6.5.

[2] BKKBN pre-prosperous and KS1 indices for December 1997 are used as instruments.

Detailed estimation results are given in table 6.19 (appendix 6.A).

Note that health card allocation data is likely to be endogenous. Unlike the JPS budget, it is not administrative data driven by pre-programme welfare indicators. It reflects the actual allocation of health cards, which depends on district specific infrastructure, organisation and welfare characteristics, and is likely to be correlated with the heterogeneous effects of the crisis.[20] Therefore, we use the BKKBN indices from December 1997 as instruments for health card allocation.[21]

[20] A similar issue arises in section 5.4.2 with the estimation of the impact of scholarships on school enrolment. There it is shown that the assumption of a constant time trend across districts is a problem when using the actual allocation of scholarships reported in the Susenas. OLS estimates are then likely to be biased, as time variant unobservables are correlated with regional variation in programme implementation.

[21] We use the indices for the two poorest BKKBN classifications (pre-prosperous and KS1). Households

The results are given in table 6.8 and suggest that our original estimates are fairly robust and capture the combined effect of the programme. When we add health card coverage, the coefficients for the JPS grants are a slightly larger and a little less precise. Neither the coefficient of the health card variable or that of the interaction term is significant.

6.5 Conclusion

This chapter presented an impact evaluation of the health card programme as it operated under the Social Safety Net in its very first months. It shows that in many ways the programme was a success. In other ways the programme has achieved things which may not have been the objective at the outset.

The health card programme has a particular design that allows both components of the programme to be treated as separate interventions, and the effectiveness of a health care cost waiver to be compared with that of a broadly targeted supply impulse. The health card entitled households to a price subsidy at public health care providers, while the facilities that provided the subsidised received budgetary support. However, there is a weak link between the financial compensation and the provision of free services to health card recipients. The budgetary support was not conditional on the actual utilisation of the health cards, but on the expected number of eligible households in the area served by the health facility.

For all households health card ownership resulted in a large substitution effect away from the private sector to the public sector, with a net increase in the overall use of outpatient medical services. A dynamic analysis further indicates that the combined JPS programme resulted in an increase of the outpatient contact rate at modern health care providers of 0.55 percentage point. In the event the programme would not have existed outpatient utilisation would have further fallen in 1999. However, the increased utilisation due to the direct health card effect only contributes about 20 percent to that. A considerable proportion of the impact of the programme seems to have been through the budgetary support for public services. If this is true, the comeback of the public sector in the provision of outpatient care can be attributed for a large part to the supply impulse induced by the increased spending under the JPS health programme.

However, the effects of both the direct health card and the supply impulse show a strong heterogeneous pattern across sub groups of the population. While the targeting

ranked in one of these groups are eligible for a health card. The instruments are not correlated with the pre-crisis trend. An over-identifying restrictions test further validates the instruments. Detailed results are given in tables 6.19 and 6.20 in appendix 6.A.

and impact of the direct health card programme is pro-poor, the total effect is not. The poor are responsive to a price subsidy but not to a supply impulse. The health card increased utilisation and led to a substitution effect from private to subsidised public care. For the non-poor, however, utilisation seems to be mainly supply driven, as the health card only affected their choice of health care provider without increasing utilisation. This also points to the potential impact that such programmes can have on the public/private mix if the design does not take those factors into account.

The impact of the programme has suffered from the weak link between reimbursements for public service providers and utilisation of the health card. Those in the poorest quintile benefited only from the programme if they received a health card, as the results indicate that they did not benefit from the supply impulse. In the end, the non-poor captured most of the benefits of the overall programme. This emphasises that in the absence of clear incentive mechanisms for health care providers, general increases in public spending are relatively ineffective in reaching the poor. A stronger link between provision of services and budget would likely have improved the targeting to the poor.

6.A Supplementary tables

Table 6.9: Propensity score estimations (logit), by region

	(1) Java & Bali	(2) Sumatra	(3) Sulawesi	(4) Kalimantan	(5) Other islands
Female head of household	0.351	0.351	0.268	0.694	-0.101
	[0.042]**	[0.076]**	[0.116]**	[0.146]**	[0.112]
Education head of household (reference = not completed)					
Primary	-0.133	-0.091	0.008	0.010	0.091
	[0.027]**	[0.050]†	[0.077]	[0.091]	[0.067]
Junior secondary	-0.326	-0.240	-0.179	-0.208	0.026
	[0.046]**	[0.069]**	[0.113]	[0.148]	[0.104]
Senior secondary	-0.706	-0.474	-0.312	-0.110	-0.089
	[0.054]**	[0.079]**	[0.120]	[0.160]	[0.108]
Higher	-1.107	-0.735	-0.438	-0.768	-0.160
	[0.115]**	[0.171]**	[0.258]†	[0.417]†	[0.207]
Head of household unemployed	0.275	0.277	0.111	-0.274	-0.370
	[0.115]*	[0.264]	[0.423]	[0.741]	[0.399]
Ln(household size)	0.313	0.360	0.284	0.314	0.287
	[0.033]**	[0.059]**	[0.091]**	[0.110]**	[0.080]**
Household composition (reference = share of males age 18-60)					
Share of males age < 18	0.533	0.296	0.178	0.443	0.779
	[0.088]**	[0.158]†	[0.248]	[0.293]	[0.221]**
Share of females age < 18	0.567	0.205	-0.100	0.357	0.705
	[0.089]**	[0.160]	[0.257]	[0.298]	[0.225]**
Share of females age 18-60	0.299	0.185	0.337	-0.231	0.560
	[0.097]**	[0.184]	[0.278]	[0.330]	[0.256]*
Share of males age > 60	0.419	0.328	0.159	1.302	0.537
	[0.094]**	[0.213]	[0.320]	[0.347]**	[0.272]*
Share of females age > 60	0.362	0.321	0.677	0.668	0.810
	[0.097]**	[0.205]	[0.308]*	[0.351]†	[0.303]**
BKKBN criteria					
Worship	-0.000	-0.176	-0.053	0.051	0.603
	[0.037]	[0.085]*	[0.105]	[0.143]	[0.177]**
Food	-0.278	-0.264	0.174	-0.528	-0.183
	[0.096]**	[0.151]†	[0.246]	[0.211]*	[0.119]
Clothing	-0.178	-0.372	-0.620	-0.753	0.241

Continued on next page...

... table 6.9 continued

	(1)	(2)	(3)	(4)	(5)
	[0.057]**	[0.107]**	[0.159]**	[0.164]**	[0.100]**
Floor	-0.201	-0.064	-0.091	-0.676	0.066
	[0.041]**	[0.075]	[0.125]	[0.163]**	[0.089]
Health	0.237	0.367	0.677	0.274	0.321
	[0.040]**	[0.075]**	[0.114]**	[0.131]*	[0.087]**
Main source of subsistence (reference = agriculture)					
Mining, quarrying	0.218	0.246	-0.056	-0.264	-0.064
	[0.135]	[0.184]	[0.411]	[0.222]	[0.548]
Processing industry	0.080	-0.054	0.226	-0.051	0.064
	[0.043]†	[0.107]	[0.138]	[0.169]	[0.165]
Electricity, gas, water	-0.397	-0.907	-0.246		0.086
	[0.354]	[0.726]	[1.031]		[0.847]
Construction	0.277	0.206	0.299	0.250	0.321
	[0.050]**	[0.109]†	[0.165]†	[0.199]	[0.165]†
Trade	-0.061	-0.167	-0.093	-0.661	-0.067
	[0.035]†	[0.076]*	[0.109]	[0.170]**	[0.122]
Transport, storage,	0.182	0.069	0.213	-0.212	-0.181
or communication	[0.050]**	[0.100]	[0.148]	[0.217]	[0.180]
Finance, real estate	-0.196	-0.805	-0.687	-1.021	-0.839
	[0.161]	[0.463]†	[0.740]	[1.023]	[0.755]
Services	0.081	0.075	-0.163	-0.031	-0.027
	[0.043]†	[0.082]	[0.131]	[0.161]	[0.108]
Other	-0.017	0.381	0.601	-1.428	0.816
	[0.175]	[0.318]	[0.567]	[1.026]	[0.852]
Income recipient	-0.197	-0.315	-0.394	-0.604	-0.033
	[0.054]**	[0.121]**	[0.160]*	[0.264]*	[0.165]
Household owns holy book	-0.083	0.213	0.071	0.178	0.344
	[0.028]**	[0.074]**	[0.100]	[0.115]	[0.070]**
Status of house (reference = own property)					
Lease	-0.495	-0.139	-0.301	-0.623	-1.093
	[0.090]**	[0.127]	[0.262]	[0.524]	[0.440]*
Rent	-0.561	0.097	-1.263	-0.884	-1.110
	[0.123]**	[0.095]	[0.466]**	[0.301]**	[0.310]**
Official	0.507	0.050	-0.205	-0.569	-0.271
	[0.131]**	[0.139]	[0.340]	[0.334]	[0.182]
Free	0.055	0.141	0.064	-0.221	0.193
	[0.065]	[0.095]	[0.152]	[0.234]	[0.170]

Continued on next page...

... table 6.9 continued

	(1)	(2)	(3)	(4)	(5)
Other	0.030	0.233	0.607	-0.327	0.072
	[0.103]	[0.158]	[0.202]**	[0.342]	[0.233]
Type of roof (reference = concrete					
Corrugated tile	0.066	-0.368	-0.256	-1.098	-0.985
	[0.113]	[0.169]*	[0.320]	[0.504]*	[0.276]**
Shingle roof	-0.344	-0.072	0.348	-0.964	-1.111
	[0.323]	[0.267]	[0.423]	[0.477]*	[0.589]†
Iron sheeting	-0.080	-0.376	-0.223	-0.819	-0.552
	[0.133]	[0.160]*	[0.267]	[0.476]†	[0.269]*
Asbestos	0.006	-0.078	-0.385	-2.108	-0.725
	[0.178]	[0.259]	[0.502]	[0.855]*	[0.455]
Sugar palm fibre	0.085	-0.481	-0.136	-0.004	-0.434
	[0.322]	[0.354]	[0.363]	[0.609]	[0.493]
Leaves, other	-0.097	0.043	0.194	-0.569	-0.795
	[0.158]	[0.172]	[0.279]	[0.479]	[0.273]**
Type of wall (reference = brick)					
Wood	0.162	0.438	0.264	0.492	0.568
	[0.036]**	[0.059]**	[0.107]	[0.227]*	[0.102]**
Bamboo	0.522	0.600	0.461	0.805	0.270
	[0.034]**	[0.097]**	[0.126]**	[0.320]*	[0.091]**
Other	0.242	0.191	0.243	0.453	0.338
	[0.145]†	[0.196]	[0.162]	[0.250]†	[0.100]**
Type of floor (reference = marble, ceramic)					
Floor tile	0.460	0.152	0.125	-0.257	0.624
	[0.059]**	[0.200]	[0.372]	[0.531]	[0.349]†
Cement plaster	0.901	0.405	0.869	0.391	0.604
	[0.057]**	[0.151]**	[0.308]**	[0.436]	[0.270]*
Wood	0.810	0.240	0.602	-0.007	0.506
	[0.101]**	[0.162]	[0.321]†	[0.420]	[0.293]†
Bamboo	1.070	0.430	0.977	0.158	0.514
	[0.100]**	[0.247]†	[0.349]**	[0.566]	[0.319]
Earth	1.137	0.575	1.073	0.443	0.817
	[0.070]**	[0.176]**	[0.337]**	[0.477]	[0.286]**
Other	0.138	0.515	0.167	1.401	1.398
	[0.234]	[0.561]	[0.578]	[0.611]*	[0.325]**
Source drinking of water (reference = bottled water)					
Tap	-0.402	0.064	0.540	1.343	0.288

Continued on next page...

... table 6.9 continued

	(1)	(2)	(3)	(4)	(5)
	[0.167]*	[0.305]	[0.487]	[1.056]	[0.515]
Pump	-0.476	0.223	-0.347	0.777	0.538
	[0.181]**	[0.338]	[0.534]	[1.144]	[0.560]
Protected well	-0.462	0.282	0.318	0.855	0.150
	[0.180]*	[0.323]	[0.518]	[1.143]	[0.558]
Unprotected well	-0.346	0.097	0.463	0.829	0.617
	[0.182]†	[0.325]	[0.522]	[1.139]	[0.558]
Protected spring	-0.393	0.396	0.631	-0.705	0.190
	[0.181]*	[0.327]	[0.518]	[1.227]	[0.556]
Unprotected spring	-0.457	0.013	0.063	0.680	0.415
	[0.184]*	[0.333]	[0.538]	[1.202]	[0.557]
River	-0.182	0.104	-0.132	0.563	0.120
	[0.205]	[0.326]	[0.560]	[1.135]	[0.561]
Rain water, other	-0.202	0.532	-0.046	0.461	-0.339
	[0.194]	[0.332]	[0.547]	[1.139]	[0.570]
Do not purchase drinking water	0.106	-0.069	0.236	0.502	-0.041
	[0.071]	[0.116]	[0.188]	[0.433]	[0.214]
Drinking water facility (reference = private)					
Shared	0.251	0.256	0.161	0.216	0.316
	[0.029]**	[0.059]**	[0.085]†	[0.136]	[0.090]**
Public	0.061	0.259	-0.186	-0.172	0.457
	[0.037]	[0.072]**	[0.106]†	[0.154]	[0.091]**
None	0.081	0.192	0.241	0.476	0.459
	[0.059]	[0.087]*	[0.141]†	[0.134]**	[0.127]**
Source of light (reference = PLN electricity)					
Non-PLN electricity	-0.199	-0.173	0.667	-1.143	0.265
	[0.124]	[0.114]	[0.200]**	[0.378]**	[0.166]
Pump lantern	-0.073	0.160	0.431	0.286	0.559
	[0.097]	[0.078]*	[0.120]**	[0.176]	[0.137]**
Oil lamp	0.019	0.308	0.131	0.183	0.145
	[0.043]	[0.061]**	[0.095]	[0.100]†	[0.080]†
Other	-0.221	0.008	-0.098	-0.068	-0.048
	[0.247]	[0.248]	[0.459]	[0.421]	[0.189]
Toilet facilities (reference = private)					
Shared	0.061	-0.000	0.078	0.596	-0.007
	[0.039]	[0.083]	[0.115]	[0.138]**	[0.115]
Public	0.320	0.419	0.639	0.755	0.213

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... table 6.9 continued

	(1)	(2)	(3)	(4)	(5)
	[0.051]**	[0.085]**	[0.167]**	[0.151]**	[0.152]
Other	0.228	0.151	0.028	-0.115	0.237
	[0.048]**	[0.077]†	[0.130]	[0.137]	[0.103]*
Toilet disposal (reference = septic tank)					
Pond, rice field	-0.045	0.417	-0.015	-0.005	0.793
	[0.063]	[0.123]**	[0.260]	[0.494]	[0.277]**
River, lake, sea	0.200	0.218	0.303	0.496	0.180
	[0.049]**	[0.085]**	[0.147]*	[0.168]**	[0.133]
Hole	0.220	0.306	0.139	0.233	0.441
	[0.036]**	[0.071]**	[0.099]	[0.156]	[0.098]**
Shore, open field	0.363	0.209	0.291	0.519	0.168
	[0.072]**	[0.112]†	[0.142]*	[0.217]*	[0.133]
Other	0.016	0.195	0.029	0.460	0.297
	[0.089]	[0.111]†	[0.185]	[0.239]†	[0.140]*
Village characteristics					
IDT village	0.066	0.205	0.103	-0.071	0.034
	[0.030]*	[0.056]**	[0.082]	[0.093]	[0.096]
Rural area	-0.159	0.243	-0.095	-0.194	0.235
	[0.039]**	[0.084]**	[0.123]	[0.186]	[0.111]*
Nr. of Puskesmas	0.004	-0.011	0.051	-0.046	-0.113
	[0.031]	[0.061]	[0.091]	[0.102]	[0.070]
Nr. of supporting Puskesmas	-0.186	-0.058	-0.051	-0.127	-0.311
	[0.025]**	[0.041]	[0.067]	[0.073]†	[0.057]**
Nr. of Polindes	-0.016	-0.137	-0.094	0.072	-0.258
	[0.028]	[0.051]**	[0.094]	[0.088]	[0.081]**
Nr. doctors per	0.236	0.131	-0.174	-0.037	0.080
1,000 inhabitant	[0.037]**	[0.046]**	[0.108]	[0.152]	[0.048]†
Nr. village midwifes per	0.326	0.193	-0.002	0.366	0.116
1,000 inhabitants	[0.067]	[0.032]**	[0.110]	[0.081]**	[0.048]*
Majority of inter village	-0.942	0.651	0.182	0.417	0.075
traffic by land	[0.378]*	[0.119]**	[0.190]	[0.112]**	[0.134]
Health facilities easy or	0.064	-0.117	-0.293	0.036	0.236
very easy to reach	[0.061]	[0.070]†	[0.115]*	[0.125]	[0.087]**
Education head of village (reference = not completed)					
Primary	-0.217	-0.375	0.015	1.189	0.499
	[0.140]	[0.141]**	[0.311]	[0.274]**	[0.154]**
Junior secondary	-0.159	-0.516	0.228	1.025	0.226

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... table 6.9 continued

	(1)	(2)	(3)	(4)	(5)
	[0.140]	[0.141]**	[0.295]	[0.277]**	[0.158]
Senior secondary	-0.117	-0.471	0.208	0.818	0.259
	[0.139]	[0.140]**	[0.293]	[0.280]**	[0.160]
Higher	-0.176	-0.420	0.365	0.774	0.472
	[0.141]	[0.156]**	[0.301]	[0.327]*	[0.179]**
BKKBN rate per sub-district	0.892	0.835	0.358	0.893	0.114
	[0.085]**	[0.162]**	[0.292]	[0.294]**	[0.185]
Constant	-2.201	-3.783	-4.565	-4.503	-6.587
	[0.493]**	[0.491]**	[0.798]**	[1.300]**	[0.777]**
District fixed effects	yes	yes	yes	yes	yes
Observations	87,061	43,381	23,779	15,697	22,441
Pseudo R-squared	0.20	0.12	0.17	0.15	0.26

Robust standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.10: Exogeneity of JPS budget data with respect to the trend in utilisation 1997 - 1998 (OLS; dependent variable: change in contact rate in districts)

	(1) All outpatient	(2) Public outpatient	(3) Private outpatient
JPS budget per capita per district	-0.0013	-0.0014	0.00003
	[0.0020]	[0.0013]	[0.00116]
Constant	-0.0252	-0.0162	-0.0077
	[0.0038]**	[0.0026]**	[0.0023]**
Observations	292	292	292
R-squared	0.0015	0.0036	0.0000
F-test model (Prob > F)	0.5081	0.3098	0.9803

Standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.11: Impact of health card on utilisation of outpatient services (direct health card effect, 3 month reference period)

	Intervention group	Control group	Difference ($\hat{\beta}$)	[s.e.][1]	% Change	Direct effect ($\hat{p}\hat{\beta}$)	$\hat{p}$	Number of observations Intervention	Control
All outpatient care									
Quintile 1 (poor)	0.1264	0.1110	0.0153	[0.0036]**	13.8	0.0028	0.185	24,901	20,283
Quintile 2	0.1475	0.1362	0.0113	[0.0045]**	8.3	0.0015	0.137	19,447	17,825
Quintile 3	0.1592	0.1420	0.0172	[0.0049]**	12.1	0.0018	0.106	15,582	15,347
Quintile 4	0.1767	0.1598	0.0170	[0.0061]**	10.6	0.0012	0.071	10,866	11,997
Quintile 5 (rich)	0.1773	0.1754	0.0019	[0.0084]**	1.1	0.0001	0.037	5,586	8,040
Male	0.1409	0.1325	0.0083	[0.0032]**	6.3	0.0009	0.105	37,854	36,437
Female	0.1566	0.1454	0.0111	[0.0033]**	7.6	0.0012	0.108	38,619	37,161
Urban	0.1615	0.1514	0.0101	[0.0049]**	6.7	0.0007	0.072	17,780	16,761
Rural	0.1440	0.1352	0.0089	[0.0025]**	6.6	0.0011	0.128	58,693	56,837
All	0.1488	0.1391	0.0098	[0.0022]**	7.0	0.0010	0.106	76,473	73,598
Public outpatient care									
Quintile 1 (poor)	0.0950	0.0710	0.0240	[0.0031]**	33.9	0.0044	0.185	24,901	20,283
Quintile 2	0.1000	0.0755	0.0245	[0.0035]**	32.4	0.0034	0.137	19,447	17,825
Quintile 3	0.1056	0.0762	0.0293	[0.0039]**	38.5	0.0031	0.106	15,582	15,347
Quintile 4	0.1115	0.0820	0.0296	[0.0047]**	36.1	0.0021	0.071	10,866	11,997
Quintile 5 (rich)	0.1146	0.0731	0.0414	[0.0063]**	56.7	0.0015	0.037	5,586	8,040
Male	0.0922	0.0697	0.0225	[0.0024]**	32.3	0.0024	0.105	37,854	36,437
Female	0.1118	0.0810	0.0308	[0.0027]**	38.1	0.0033	0.108	38,619	37,161
Urban	0.1030	0.0734	0.0296	[0.0038]**	40.4	0.0021	0.072	17,780	16,761
Rural	0.1018	0.0760	0.0258	[0.0020]**	34.0	0.0033	0.128	58,693	56,837
All	0.1021	0.0754	0.0268	[0.0018]**	35.5	0.0028	0.106	76,473	73,598
Private outpatient care									
Quintile 1 (poor)	0.0313	0.0400	-0.0087	[0.0021]**	−21.8	-0.0016	0.185	24,901	20,283
Quintile 2	0.0475	0.0608	-0.0132	[0.0031]**	−21.7	-0.0018	0.137	19,447	17,825
Quintile 3	0.0537	0.0658	-0.0121	[0.0034]**	−18.4	-0.0013	0.106	15,582	15,347
Quintile 4	0.0652	0.0778	-0.0126	[0.0042]**	−16.2	-0.0009	0.071	10,866	11,997
Quintile 5 (rich)	0.0627	0.1023	-0.0396	[0.0068]**	−38.7	-0.0015	0.037	5,586	8,040
Male	0.0486	0.0629	-0.0142	[0.0023]**	−22.6	-0.0015	0.105	37,854	36,437
Female	0.0447	0.0645	-0.0197	[0.0022]**	−30.6	-0.0021	0.108	38,619	37,161
Urban	0.0585	0.0780	-0.0195	[0.0039]**	−25.0	-0.0014	0.072	17,780	16,761
Rural	0.0422	0.0592	-0.0169	[0.0016]**	−28.6	-0.0022	0.128	58,693	56,837
All	0.0467	0.0637	-0.0170	[0.0014]**	−26.7	-0.0018	0.106	76,473	73,598

[1] Bootstrapped standard errors with 500 replications.
Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.12: Total effect of JPS budget allocation on change in use of outpatient care (public and private)

	(1) All	(2) Q1	(3) Q2	(4) Q3	(5) Q4	(6) Q5	(7) Male	(8) Female	(9) Urban	(10) Rural
JPS budget per capita	0.0039	0.0039	0.0073	0.0012	0.0065	0.0075	0.0037	0.0040	0.0045	0.0060
	[0.0022]†	[0.0041]	[0.0038]†	[0.0029]	[0.0032]*	[0.0036]*	[0.0022]†	[0.0024]†	[0.0048]	[0.0028]*
Diff. age	-0.0028	-0.0023	-0.0109	0.0004	-0.0030	0.0002	-0.0047	-0.0007	0.0044	-0.0011
	[0.0031]	[0.0059]	[0.0053]*	[0.0041]	[0.0045]	[0.0051]	[0.0032]	[0.0034]	[0.0061]	[0.0040]
Diff. household size	0.0073	-0.0056	-0.0394	-0.0025	0.0185	0.0144	0.0059	0.0089	-0.0140	0.0153
	[0.0121]	[0.0230]	[0.0207]†	[0.0158]	[0.0175]	[0.0200]	[0.0123]	[0.0130]	[0.0233]	[0.0155]
Diff. % rural population	0.0032	0.0600	0.0107	-0.0409	0.0112	0.0792	-0.0042	0.0103	-0.0069	0.0078
	[0.0306]	[0.0601]	[0.0522]	[0.0399]	[0.0441]	[0.0504]	[0.0310]	[0.0329]	[0.0636]	[0.0381]
Diff. population	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Diff. poverty rate	-0.0065	-0.0200	0.0375	0.0436	0.0172	0.0281	-0.0074	-0.0060	-0.0193	-0.0187
	[0.0182]	[0.0339]	[0.0310]	[0.0237]†	[0.0262]	[0.0299]	[0.0184]	[0.0195]	[0.0350]	[0.0228]
Diff. poverty gap	0.0387	-0.0121	0.0330	0.0579	0.0554	0.0445	0.0272	0.0495	0.0245	0.0302
	[0.0159]*	[0.0300]	[0.0272]	[0.0208]**	[0.0230]*	[0.0263]†	[0.0161]†	[0.0172]**	[0.0306]	[0.0205]
Sumatra	0.0001	-0.0062	-0.0038	0.0035	-0.0016	-0.0070	0.0004	-0.0002	-0.0129	0.0032
	[0.0049]	[0.0092]	[0.0083]	[0.0064]	[0.0071]	[0.0081]	[0.0050]	[0.0053]	[0.0093]	[0.0063]
Sulawesi	-0.0203	-0.0156	-0.0182	-0.0178	-0.0274	-0.0202	-0.0168	-0.0236	-0.0307	-0.0192
	[0.0063]**	[0.0118]	[0.0108]†	[0.0082]*	[0.0091]**	[0.0104]†	[0.0064]**	[0.0068]**	[0.0122]*	[0.0081]*
Kalimantan	-0.0044	0.0013	-0.0036	-0.0047	0.0044	-0.0111	-0.0039	-0.0050	-0.0060	0.0021
	[0.0067]	[0.0125]	[0.0114]	[0.0087]	[0.0096]	[0.0110]	[0.0068]	[0.0072]	[0.0129]	[0.0084]
Other islands	0.0041	-0.0134	-0.0139	0.0105	-0.0068	-0.0135	0.0041	0.0044	-0.0259	0.0017
	[0.0080]	[0.0151]	[0.0137]	[0.0105]	[0.0116]	[0.0133]	[0.0081]	[0.0087]	[0.0157]	[0.0101]
Constant	-0.0151	0.0087	-0.0173	-0.0281	-0.0301	-0.0279	-0.0103	-0.0197	-0.0103	-0.0155
	[0.0087]†	[0.0164]	[0.0148]	[0.0113]*	[0.0125]*	[0.0143]†	[0.0088]	[0.0094]*	[0.0170]	[0.0112]
Observations	293	290	293	293	293	293	293	293	286	276
R-squared	0.08	0.02	0.07	0.07	0.07	0.05	0.07	0.10	0.03	0.06

Standard errors in brackets.
Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.13: Total effect of JPS budget allocation on change in use of public outpatient care

	(1) All	(2) Q1	(3) Q2	(4) Q3	(5) Q4	(6) Q5	(7) Male	(8) Female	(9) Urban	(10) Rural
JPS budget per capita	0.0033	0.0035	0.0080	-0.0001	0.0059	0.0094	0.0026	0.0040	0.0016	0.0053
	[0.0015]*	[0.0033]	[0.0033]*	[0.0022]	[0.0023]*	[0.0023]**	[0.0014]†	[0.0017]*	[0.0032]	[0.0020]**
Diff. age	-0.0028	-0.0022	-0.0122	-0.0019	-0.0035	-0.0012	-0.0038	-0.0017	-0.0019	-0.0005
	[0.0021]	[0.0047]	[0.0047]*	[0.0031]	[0.0033]	[0.0032]	[0.0020]†	[0.0024]	[0.0041]	[0.0028]
Diff. household size	0.0029	-0.0088	-0.0353	-0.0079	0.0075	-0.0032	0.0033	0.0029	-0.0127	0.0119
	[0.0081]	[0.0184]	[0.0184]†	[0.0119]	[0.0127]	[0.0125]	[0.0077]	[0.0092]	[0.0156]	[0.0110]
Diff. % rural population	0.0252	0.0787	0.0246	-0.0555	0.0476	0.1037	0.0075	0.0426	-0.0136	-0.0015
	[0.0203]	[0.0481]	[0.0464]	[0.0300]†	[0.0321]	[0.0314]**	[0.0194]	[0.0233]†	[0.0427]	[0.0271]
Diff. population	0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Diff. poverty rate	0.0082	-0.0058	0.0077	0.0407	0.0082	0.0034	0.0047	0.0114	-0.0070	0.0100
	[0.0121]	[0.0272]	[0.0275]	[0.0178]*	[0.0191]	[0.0186]	[0.0115]	[0.0138]	[0.0235]	[0.0163]
Diff. poverty gap	0.0356	-0.0027	0.0174	0.0476	0.0366	0.0133	0.0240	0.0464	0.0179	0.0343
	[0.0106]**	[0.0240]	[0.0242]	[0.0156]**	[0.0167]*	[0.0164]	[0.0101]*	[0.0122]**	[0.0205]	[0.0146]*
Sumatra	-0.0015	-0.0005	-0.0099	0.0024	0.0006	-0.0055	-0.0030	0.0000	-0.0157	0.0039
	[0.0032]	[0.0074]	[0.0074]	[0.0048]	[0.0051]	[0.0050]	[0.0031]	[0.0037]	[0.0062]*	[0.0045]
Sulawesi	-0.0153	-0.0121	-0.0186	-0.0151	-0.0203	-0.0171	-0.0136	-0.0170	-0.0236	-0.0153
	[0.0042]**	[0.0094]	[0.0096]†	[0.0062]*	[0.0066]**	[0.0065]**	[0.0040]**	[0.0048]**	[0.0082]**	[0.0057]**
Kalimantan	0.0013	0.0066	-0.0003	-0.0007	0.0053	-0.0033	0.0008	0.0017	-0.0037	0.0052
	[0.0044]	[0.0100]	[0.0101]	[0.0066]	[0.0070]	[0.0069]	[0.0042]	[0.0051]	[0.0087]	[0.0060]
Other islands	-0.0011	-0.0122	-0.0214	0.0019	-0.0137	-0.0277	0.0003	-0.0023	-0.0269	-0.0005
	[0.0053]	[0.0121]	[0.0122]†	[0.0079]	[0.0084]	[0.0083]**	[0.0051]	[0.0061]	[0.0105]*	[0.0072]
Constant	-0.0128	0.0054	-0.0055	-0.0180	-0.0170	-0.0125	-0.0071	-0.0182	-0.0007	-0.0192
	[0.0058]*	[0.0131]	[0.0132]	[0.0085]*	[0.0091]†	[0.0089]	[0.0055]	[0.0066]**	[0.0114]	[0.0079]*
Observations	293	290	293	293	293	293	293	293	286	276
R-squared	0.11	0.02	0.07	0.09	0.08	0.10	0.09	0.12	0.06	0.09

Standard errors in brackets.
Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.14: Total effect of JPS budget allocation on change in use of private outpatient care

	(1) All	(2) Q1	(3) Q2	(4) Q3	(5) Q4	(6) Q5	(7) Male	(8) Female	(9) Urban	(10) Rural
JPS budget per capita	0.0009	0.0020	-0.0002	0.0016	0.0004	-0.0016	0.0012	0.0005	0.0031	0.0013
	[0.0013]	[0.0025]	[0.0018]	[0.0017]	[0.0020]	[0.0028]	[0.0014]	[0.0014]	[0.0031]	[0.0017]
Diff. age	-0.0000	-0.0019	-0.0004	0.0039	0.0012	0.0004	-0.0012	0.0012	0.0065	-0.0004
	[0.0019]	[0.0035]	[0.0026]	[0.0024]	[0.0029]	[0.0040]	[0.0020]	[0.0020]	[0.0039]†	[0.0025]
Diff. household size	0.0085	0.0017	-0.0026	0.0106	0.0158	0.0257	0.0085	0.0085	0.0045	0.0064
	[0.0074]	[0.0137]	[0.0101]	[0.0095]	[0.0111]	[0.0156]	[0.0078]	[0.0077]	[0.0148]	[0.0096]
Diff. % rural population	-0.0269	-0.0061	-0.0141	0.0119	-0.0370	-0.0289	-0.0285	-0.0253	-0.0002	0.0103
	[0.0187]	[0.0358]	[0.0255]	[0.0240]	[0.0280]	[0.0394]	[0.0197]	[0.0195]	[0.0404]	[0.0236]
Diff. population	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	[0.0000]	[0.0000]	[0.0000]**	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Diff. poverty rate	-0.0195	-0.0219	0.0267	0.0054	0.0086	0.0158	-0.0178	-0.0213	-0.0153	-0.0352
	[0.0111]†	[0.0202]	[0.0151]†	[0.0142]	[0.0166]	[0.0234]	[0.0117]	[0.0116]†	[0.0222]	[0.0142]*
Diff. poverty gap	0.0039	-0.0256	0.0194	0.0191	0.0262	0.0265	0.0027	0.0052	0.0012	-0.0033
	[0.0097]	[0.0179]	[0.0133]	[0.0125]	[0.0146]†	[0.0206]	[0.0103]	[0.0102]	[0.0194]	[0.0127]
Sumatra	0.0017	-0.0038	0.0054	0.0014	-0.0017	-0.0014	0.0034	-0.0000	0.0025	-0.0004
	[0.0030]	[0.0055]	[0.0041]	[0.0038]	[0.0045]	[0.0063]	[0.0032]	[0.0031]	[0.0059]	[0.0039]
Sulawesi	-0.0061	-0.0028	-0.0015	-0.0044	-0.0090	-0.0045	-0.0044	-0.0079	-0.0108	-0.0053
	[0.0039]	[0.0070]	[0.0053]	[0.0049]	[0.0058]	[0.0082]	[0.0041]	[0.0040]†	[0.0078]	[0.0050]
Kalimantan	-0.0063	-0.0042	-0.0030	-0.0056	-0.0001	-0.0065	-0.0054	-0.0073	-0.0034	-0.0037
	[0.0041]	[0.0074]	[0.0056]	[0.0052]	[0.0061]	[0.0086]	[0.0043]	[0.0043]†	[0.0082]	[0.0052]
Other islands	0.0069	-0.0023	0.0072	0.0101	0.0101	0.0187	0.0068	0.0070	0.0024	0.0030
	[0.0049]	[0.0090]	[0.0067]	[0.0063]	[0.0074]	[0.0104]†	[0.0052]	[0.0051]	[0.0100]	[0.0063]
Constant	-0.0029	0.0086	-0.0134	-0.0159	-0.0175	-0.0141	-0.0028	-0.0031	-0.0078	0.0027
	[0.0053]	[0.0098]	[0.0072]†	[0.0068]*	[0.0080]*	[0.0112]	[0.0056]	[0.0056]	[0.0108]	[0.0069]
Observations	293	290	293	293	293	293	293	293	286	276
R-squared	0.06	0.02	0.07	0.06	0.05	0.03	0.06	0.06	0.03	0.04

Standard errors in brackets.
Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Table 6.15: Sensitivity direct effect estimate, outpatient care (one month recall; probit marginal effects

	(1)	(2)	(3)
Health card	0.0109**	0.0106*	0.0114**
	[0.0020]	[0.0052]	[0.0021]
Health card × JPS per capita		0.0034	
		[0.0025]	
Health card × health card coverage		-0.0289	
		[0.0188]	
Health card × JPS per health card			-0.0001
			[0.0000]
Age	0.0007**	0.0007**	0.0007**
	[0.0001]	[0.0001]	[0.0001]
Female	0.0075**	0.0075**	0.0076**
	[0.0020]	[0.0020]	[0.0020]
Female head of household	-0.0115**	-0.0115**	-0.0116**
	[0.0031]	[0.0031]	[0.0031]
Education head of household			
Primary	-0.0025	-0.0025	-0.0027
	[0.0022]	[0.0022]	[0.0022]
Junior secondary	0.0069†	0.0069†	0.0063
	[0.0042]	[0.0042]	[0.0042]
Senior secondary	0.0103*	0.0102*	0.0095*
	[0.0044]	[0.0044]	[0.0044]
Higher	0.0489*	0.0486*	0.0472*
	[0.0211]	[0.0211]	[0.0207]
Ln(household size)	-0.0381**	-0.0380**	-0.0382**
	[0.0026]	[0.0026]	[0.0026]
BKKBN criteria			
Worship	0.0126**	0.0125**	0.0130**
	[0.0030]	[0.0030]	[0.0030]
Food	-0.0086	-0.0088	-0.0075
	[0.0076]	[0.0076]	[0.0075]
Clothing	0.0061	0.0061	0.0084†

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... table 6.15 continued

	(1)	(2)	(3)
	[0.0047]	[0.0047]	[0.0047]
Floor	0.0024	0.0024	-0.0005
	[0.0022]	[0.0022]	[0.0023]
Health	0.0494**	0.0493**	0.0505**
	[0.0028]	[0.0028]	[0.0028]
Agriculture main source of income	-0.0220**	-0.0220**	-0.0224**
	[0.0023]	[0.0023]	[0.0023]
Village characteristics			
Rural area	-0.0102**	-0.0103**	-0.0080**
	[0.0031]	[0.0030]	[0.0030]
IDT village	-0.0037	-0.0036	-0.0019
	[0.0023]	[0.0023]	[0.0022]
Nr. of Puskesmas	0.0119**	0.0119**	0.0109**
	[0.0025]	[0.0025]	[0.0025]
Nr. of supporting Puskesmas	0.0081**	0.0081**	0.0073**
	[0.0020]	[0.0020]	[0.0020]
BKKBN rate per sub-district	-0.0269**	-0.0270**	0.0014
	[0.0060]	[0.0060]	[0.0053]
JPS per capita in district	0.0126**	0.0112**	
	[0.0016]	[0.0020]	
Health card coverage in district	0.1059**	0.1195**	
	[0.0109]	[0.0146]	
JPS per health card in district			0.0000
			[0.0000]
Poverty rate in district	-0.0179**	-0.0181**	0.0139*
	[0.0067]	[0.0067]	[0.0060]
Poverty gap in district	-0.0041	-0.0029	0.0277**
	[0.0106]	[0.0106]	[0.0103]
Observations	150,889	150,889	150,424
Pseudo R-squared	0.02	0.02	0.01

Standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.16: Sensitivity direct effect estimate, public care (one month recall; probit marginal effects

	(1)	(2)	(3)
Health card	0.0235**	0.0272**	0.0239**
	[0.0015]	[0.0038]	[0.0016]
Health card × JPS per capita		-0.0015	
		[0.0019]	
Health card × health card coverage		-0.0059	
		[0.0137]	
Health card × JPS per health card			-0.0000
			[0.0000]
Age	0.0002**	0.0002**	0.0002**
	[0.0000]	[0.0000]	[0.0000]
Female	0.0097**	0.0097**	0.0097**
	[0.0015]	[0.0015]	[0.0015]
Female head of household	-0.0065**	-0.0065**	-0.0065**
	[0.0024]	[0.0024]	[0.0024]
Education head of household			
Primary	-0.0040*	-0.0040*	-0.0043*
	[0.0017]	[0.0017]	[0.0017]
Junior secondary	0.0003	0.0002	0.0001
	[0.0030]	[0.0030]	[0.0030]
Senior secondary	-0.0012	-0.0012	-0.0011
	[0.0032]	[0.0032]	[0.0032]
Higher	-0.0229**	-0.0229**	-0.0227**
	[0.0059]	[0.0059]	[0.0060]
Ln(household size)	-0.0234**	-0.0234**	-0.0233**
	[0.0020]	[0.0020]	[0.0020]
BKKBN criteria			
Worship	0.0154**	0.0153**	0.0161**
	[0.0022]	[0.0022]	[0.0022]
Food	-0.0133*	-0.0132*	-0.0137*
	[0.0062]	[0.0062]	[0.0062]
Clothing	-0.0039	-0.0039	-0.0028

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... table 6.16 continued

	(1)	(2)	(3)
	[0.0040]	[0.0039]	[0.0039]
Floor	0.0044**	0.0044*	0.0029†
	[0.0017]	[0.0017]	[0.0017]
Health	0.0307**	0.0307**	0.0311**
	[0.0021]	[0.0021]	[0.0021]
Agriculture main source of income	-0.0125**	-0.0125**	-0.0124**
	[0.0017]	[0.0017]	[0.0018]
Village characteristics			
Rural area	-0.0027	-0.0027	-0.0006
	[0.0023]	[0.0023]	[0.0022]
IDT village	0.0021	0.0020	0.0043*
	[0.0017]	[0.0017]	[0.0017]
Nr. of Puskesmas	0.0098**	0.0098**	0.0094**
	[0.0019]	[0.0019]	[0.0019]
Nr. of supporting Puskesmas	0.0118**	0.0119**	0.0116**
	[0.0015]	[0.0015]	[0.0015]
BKKBN rate per sub-district	-0.0199**	-0.0198**	-0.0015
	[0.0041]	[0.0041]	[0.0038]
JPS per capita in district	0.0119**	0.0125**	
	[0.0012]	[0.0015]	
Health card coverage in district	0.0470**	0.0507**	
	[0.0077]	[0.0114]	
JPS per health card in district			0.0000†
			[0.0000]
Poverty rate in district	-0.0087†	-0.0090†	0.0142**
	[0.0051]	[0.0051]	[0.0045]
Poverty gap in district	0.0261**	0.0258**	0.0474**
	[0.0077]	[0.0077]	[0.0076]
Observations	150,889	150,889	150,424
Pseudo R-squared	0.02	0.02	0.01

Standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.17: Sensitivity direct effect estimate, private care (one month recall; probit marginal effects

	(1)	(2)	(3)
Health card	-0.0113**	-0.0140**	-0.0109**
	[0.0015]	[0.0038] ‘	[0.0016]
Health card × JPS per capita		0.0035†	
		[0.0019]	
Health card × health card coverage		-0.0161	
		[0.0140]	
Health card × JPS per health card			-0.0001
			[0.0001]
Age	0.0006**	0.0006**	0.0006**
	[0.0000]	[0.0000]	[0.0000]
Female	-0.0022	-0.0022	-0.0022
	[0.0014]	[0.0014]	[0.0014]
Female head of household	-0.0072**	-0.0073**	-0.0073**
	[0.0021]	[0.0021]	[0.0021]
Education head of household			
Primary	0.0009	0.0009	0.0009
	[0.0016]	[0.0016]	[0.0016]
Junior secondary	0.0057†	0.0057†	0.0053†
	[0.0032]	[0.0032]	[0.0032]
Senior secondary	0.0117**	0.0117**	0.0110**
	[0.0033]	[0.0033]	[0.0033]
Higher	0.0685**	0.0682**	0.0666**
	[0.0210]	[0.0210]	[0.0206]
Ln(household size)	-0.0184**	-0.0183**	-0.0186**
	[0.0018]	[0.0018]	[0.0018]
BKKBN criteria			
Worship	-0.0017	-0.0017	-0.0020
	[0.0022]	[0.0022]	[0.0022]
Food	0.0034	0.0032	0.0044
	[0.0049]	[0.0049]	[0.0048]
Clothing	0.0106**	0.0106**	0.0117**

Continued on next page...

... table 6.17 continued

	(1)	(2)	(3)
	[0.0031]	[0.0031]	[0.0031]
Floor	-0.0013	-0.0013	-0.0027†
	[0.0016]	[0.0016]	[0.0016]
Health	0.0210**	0.0210**	0.0218**
	[0.0020]	[0.0020]	[0.0019]
Agriculture main source of income	-0.0118**	-0.0118**	-0.0123**
	[0.0016]	[0.0016]	[0.0016]
Village characteristics			
Rural area	-0.0076**	-0.0077**	-0.0074**
	[0.0022]	[0.0022]	[0.0023]
IDT village	-0.0061**	-0.0060**	-0.0061**
	[0.0016]	[0.0016]	[0.0016]
Nr. of Puskesmas	0.0022	0.0022	0.0016
	[0.0018]	[0.0018]	[0.0018]
Nr. of supporting Puskesmas	-0.0039**	-0.0039**	-0.0044**
	[0.0014]	[0.0014]	[0.0014]
BKKBN rate per sub-district	-0.0066	-0.0066	0.0055
	[0.0046]	[0.0046]	[0.0040]
JPS per capita in district	0.0014	-0.0000	
	[0.0012]	[0.0014]	
Health card coverage in district	0.0693**	0.0760**	
	[0.0082]	[0.0101]	
JPS per health card in district			-0.0001
			[0.0000]
Poverty rate in district	-0.0155**	-0.0155**	-0.0038
	[0.0047]	[0.0047]	[0.0043]
Poverty gap in district	-0.0336**	-0.0328**	-0.0200**
	[0.0078]	[0.0078]	[0.0075]
Observations	150,889	150,889	150,424
Pseudo R-squared	0.03	0.03	0.03

Standard errors in brackets.

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Table 6.18: Sensitivity direct effect estimate to selection on needs bias (pure health card effect, one month reference period)

	Intervention group	Control group	Difference ($\hat{\beta}$)	[s.e.][1]	% Change	Direct effect ($\hat{p}\hat{\beta}$)	$\hat{p}$	Number of observations Intervention	Control
All outpatient care									
Quintile 1 (poor)	0.0993	0.0866	0.0127	[0.0031]**	14.7	0.0023	0.184	25,046	20,796
Quintile 2	0.1205	0.1056	0.0149	[0.0041]**	14.1	0.0020	0.137	19,611	17,658
Quintile 3	0.1330	0.1197	0.0132	[0.0047]**	11.0	0.0014	0.106	15,655	15,393
Quintile 4	0.1450	0.1378	0.0072	[0.0058]	5.2	0.0005	0.071	10,912	12,374
Quintile 5 (rich)	0.1509	0.1468	0.0041	[0.0076]	2.8	0.0002	0.037	5,641	7,942
Male	0.1155	0.1097	0.0059	[0.0028]*	5.4	0.0006	0.105	38,085	36,843
Female	0.1269	0.1167	0.0102	[0.0029]**	8.8	0.0011	0.107	38,871	37,420
Urban	0.1390	0.1316	0.0074	[0.0049]	5.6	0.0005	0.073	17,879	17,048
Rural	0.1147	0.1073	0.0074	[0.0022]**	6.9	0.0009	0.128	59,077	57,215
All	0.1213	0.1132	0.0081	[0.0020]**	7.1	0.0009	0.106	76,956	74,263
Public outpatient care									
Quintile 1 (poor)	0.0729	0.0534	0.0195	[0.0025]**	36.5	0.0036	0.184	25,046	20,796
Quintile 2	0.0784	0.0577	0.0207	[0.0032]**	35.9	0.0028	0.137	19,611	17,658
Quintile 3	0.0855	0.0614	0.0240	[0.0036]**	39.2	0.0025	0.106	15,655	15,393
Quintile 4	0.0914	0.0685	0.0230	[0.0044]**	33.5	0.0016	0.071	10,912	12,374
Quintile 5 (rich)	0.0840	0.0665	0.0175	[0.0056]**	26.3	0.0006	0.037	5,641	7,942
Male	0.0732	0.0561	0.0171	[0.0022]**	30.5	0.0018	0.105	38,085	36,843
Female	0.0871	0.0639	0.0231	[0.0023]**	36.1	0.0025	0.107	38,871	37,420
Urban	0.0867	0.0681	0.0187	[0.0036]**	27.4	0.0014	0.073	17,879	17,048
Rural	0.0778	0.0575	0.0203	[0.0017]**	35.3	0.0026	0.128	59,077	57,215
All	0.0802	0.0601	0.0201	[0.0016]**	33.5	0.0021	0.106	76,956	74,263
Private outpatient care									
Quintile 1 (poor)	0.0305	0.0374	-0.0069	[0.0020]**	−18.3	-0.0013	0.184	25,046	20,796
Quintile 2	0.0495	0.0544	-0.0048	[0.0029]†	−8.9	-0.0007	0.137	19,611	17,658
Quintile 3	0.0572	0.0655	-0.0083	[0.0035]*	−12.7	-0.0009	0.106	15,655	15,393
Quintile 4	0.0654	0.0796	-0.0142	[0.0043]*	−17.8	-0.0010	0.071	10,912	12,374
Quintile 5 (rich)	0.0803	0.0941	-0.0138	[0.0062]*	−14.6	-0.0005	0.037	5,641	7,942
Male	0.0500	0.0606	-0.0106	[0.0022]**	−17.5	-0.0011	0.105	38,085	36,843
Female	0.0478	0.0605	-0.0127	[0.0021]**	−21.1	-0.0014	0.107	38,871	37,420
Urban	0.0613	0.0706	-0.0092	[0.0037]**	−13.1	-0.0007	0.073	17,879	17,048
Rural	0.0442	0.0574	-0.0132	[0.0016]**	−22.9	-0.0017	0.128	59,077	57,215
All	0.0489	0.0606	-0.0117	[0.0015]**	−19.3	-0.0012	0.106	76,956	74,263

[1] Bootstrapped standard errors with 500 replications.
Significance levels: † : 10% $*$: 5% $**$: 1%

Table 6.19: Sensitivity total effect estimate (IV)

	Outpatient		Public		Private	
	(1)	(2)	(3)	(4)	(5)	(6)
JPS per capita in district	0.0042	0.0044	0.0037	0.0039	0.0007	0.0007
	[0.0028]	[0.0032]	[0.0019]*	[0.0022]†	[0.0017]	[0.0020]
Health card coverage in district	-0.0118		-0.0159		0.0081	
	[0.0628]		[0.0421]		[0.0381]	
JPS per capita × health card coverage		-0.0054		-0.0060		0.0020
		[0.0244]		[0.0163]		[0.0148]
Diff. age	-0.0028	-0.0028	-0.0029	-0.0028	0.0000	-0.0000
	[0.0032]	[0.0032]	[0.0021]	[0.0021]	[0.0019]	[0.0019]
Diff. household size	0.0081	0.0083	0.0039	0.0040	0.0080	0.0082
	[0.0128]	[0.0129]	[0.0086]	[0.0086]	[0.0078]	[0.0078]
Diff. % rural population	0.0033	0.0034	0.0254	0.0255	-0.0270	-0.0269
	[0.0308]	[0.0308]	[0.0207]	[0.0206]	[0.0187]	[0.0187]
Diff. population	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Diff. poverty rate	-0.0060	-0.0063	0.0088	0.0084	-0.0198	-0.0196
	[0.0184]	[0.0183]	[0.0124]	[0.0122]	[0.0112]†	[0.0111]†
Diff. poverty gap	0.0385	0.0381	0.0353	0.0349	0.0040	0.0041
	[0.0161]*	[0.0163]*	[0.0108]**	[0.0109]**	[0.0098]	[0.0099]
Sumatra	-0.0007	-0.0005	-0.0025	-0.0022	0.0022	0.0019
	[0.0064]	[0.0057]	[0.0043]	[0.0038]	[0.0039]	[0.0035]

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... table 6.19 continued

	Outpatient		Public		Private	
	(1)	(2)	(3)	(4)	(5)	(6)
Sulawesi	-0.0214	-0.0213	-0.0169	-0.0164	-0.0053	-0.0058
	[0.0090]*	[0.0078]**	[0.0060]**	[0.0052]**	[0.0054]	[0.0047]
Kalimantan	-0.0055	-0.0053	-0.0003	0.0003	-0.0056	-0.0060
	[0.0090]	[0.0079]	[0.0060]	[0.0053]	[0.0055]	[0.0048]
Other islands	0.0029	0.0036	-0.0027	-0.0017	0.0077	0.0071
	[0.0102]	[0.0085]	[0.0068]	[0.0057]	[0.0062]	[0.0051]
Constant	-0.0138	-0.0143	-0.0110	-0.0119	-0.0038	-0.0032
	[0.0113]	[0.0095]	[0.0076]	[0.0063]†	[0.0068]	[0.0058]
Observations	293	293	293	293	293	293
R-squared	0.08	0.08	0.09	0.09	0.06	0.06
Instrumented	HC	JPS × HC	HC	JPS × HC	HC	JPS × HC
Over-identifying restrictions test						
χ-squared (1)	0.110	0.096	0.009	0.018	0.662	0.690
Probability	0.741	0.756	0.923	0.893	0.416	0.406
Durbin-Wu-Hausman test						
F (1, 279)	1.667	1.592	3.784	3.888	0.027	0.008
Probability	0.198	0.208	0.053	0.050	0.870	0.928

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... table 6.19 continued

	Outpatient		Public		Private	
	(1)	(2)	(3)	(4)	(5)	(6)
First stage regression	HC	JPS × HC				
Instruments						
BKKBN pre-prosperous	0.2315	0.5833				
	[0.0347]**	[0.0823]**				
BKKBN KS1	0.0285	-0.0187				
	[0.0535]	[0.1270]				
	(other results omitted)					
Joint significance instruments						
F (2, 279)	22.807	26.786				
Probability	0.000	0.000				

Standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 6.20: Exogeneity of BKKBN data with respect to the trend in utilisation 1997 - 1998 (OLS; dependent variable: change in contact rate in districts)

	(1) All outpatient	(2) Public outpatient	(3) Private outpatient
BKKBN pre-prosperous	-0.0045	-0.0027	-0.0030
	[0.0111]	[0.0076]	[0.0066]
BKKBN prosperous I	-0.0143	-0.0182	-0.0006
	[0.0190]	[0.0130]	[0.0113]
Constant	-0.0230	-0.0135	-0.0070
	[0.0056]**	[0.0038]**	[0.0033]**
Observations	292	292	292
R-squared	0.0024	0.0070	0.0007
F-test model (Prob > F)	0.7051	0.3622	0.9029

Standard errors in brackets.

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Chapter 7

Summary and Conclusions

This dissertation investigates the effectiveness of targeted interventions in health and education as a tool to protect access to these services for the poor in times of economic crisis, using Indonesia as case study. In particular, it investigates whether narrowly targeted interventions are suitable in crisis situations, when policy makers are faced with severe information and time constraints, and how these demand side interventions compare with broadly targeted, supply side programmes.

In 1997 Indonesia experienced a severe economic crisis that saw GPD drop by about 14 percent in 1998, strong increases in poverty, rising food prices and sharp budget cuts in social sectors. **Chapter 2** gives an account of the consequences of these events for the delivery of public services, and describes the changes in health care utilisation and school enrolment during the crisis, on the basis of Indonesia's main socioeconomic household survey - *Susenas*. The crisis seems to have slowed down the positive trend in enrolment that was observed before the crisis, and there is some evidence that children were temporarily taken out of school. The effects on education were largest with the rural poor. However, in 1999 enrolment rates recovered, reaching levels higher than before the crisis.

Outpatient health care utilisation decreased during the crisis, as real household income diminished and quality of health services deteriorated. Utilisation of both public and private outpatient care decreased for all income groups. The main explanation is that quality and supply of public care suffered considerably from the crisis, turning people away from the public sector. The public sector saw a comeback in 1999, while utilisation of private care did not recover.

In August 1998 two nationwide health and education programmes were introduced, both of which were part of the larger Indonesian Social Safety Net - *Jaring Pengaman Sosial* (JPS). These two components of the JPS intervention aimed to protect access to health and education for the poor during the crisis. The design and implementation of these health and education programmes are discussed in **chapter 3**.

The education programme consisted of a cash transfer programme, under which almost 4 million scholarships were awarded to primary and secondary school students. The size of the scholarship increased with the school level, amounting to about 7 to 18 percent of average per capita household consumption.

The health care intervention included both a targeted price subsidy and a public spending component. Health cards were targeted to households that were thought to be most vulnerable to economic shocks. The health cards entitled all household members to the price subsidy at public health care providers. Health care facilities that provided the subsidised care received extra budgetary support to compensate for the increased demand. However, there was a loose relationship between the utilisation of the health card and the compensation that the health care providers received in return. Service providers were reimbursed using a lump sum transfer based on the estimated number of poor households in their area of influence. As a result, serving a health card owner did not result in a direct financial reward to the service provider.

Both programmes followed a partly decentralised allocation process, involving both geographic and community based individual targeting. Poorer districts received relatively more scholarships and health cards. Within the districts the programme benefits were targeted to schools and health care facilities in village communities, which in turn selected the students and households.

The programmes have been implemented at a remarkable speed. By the time of the 1999 Susenas, February 1999, approximately 22 million people (about 11 percent of Indonesians) lived in households that received a health card, and 2.1 million children aged 10 to 18 (about 5 percent) had received a scholarship. The decentralised programme design may well have facilitated this swift reaction, by relying on existing administrative and operational infrastructure within the districts. However, at such short notice there was no reliable data on the impact of the crisis across districts. Geographic targeting criteria were therefore based on pre-crisis poverty estimates, which reflect the actual level of poverty to some extent but do not capture the impact of the crisis. This introduced some degree of targeting error as there appears to be no correlation between the initial level of poverty and the impact of the crisis. Moreover, relative prices had changed during the crisis, which are not accounted for in the targeting design when applying the pre-crisis poverty estimates as allocation rule.

Targeting performance of scholarships differed strongly between school levels. At primary and junior secondary level targeting was pro-poor, but with considerable leakage to wealthier groups. At senior secondary school the scholarships were not allocated pro-poor at all, but instead distributed quite evenly across the per capita consumption quintiles.

The health card programme was pro-poor in the sense that the poor had a higher probability of receiving a health card and using it to obtain free health services, presumably making them healthier. However, despite pro-poor targeting, a large number of health cards went to households in the richer quintiles. Service providers also seem to have distributed health cards based on health status and to patients that show up to ask for services.

A notable finding is that some health card owners did not use their health card when obtaining care from public service providers. It seems like several factors are in play. The particular design resulted in a discrepancy between health card ownership and utilisation. High rejection rates could follow from the delays in the lump sum transfers made to the providers. Patients could also perceive health care obtained using a health card to be inferior to the service and medicines given to patients who pay the normal user fees.

Utilisation of services is less pro-poor than ownership. Conditional on ownership, the rich have a higher propensity to use their health card, suggesting that barriers to access to health care are not fully overcome by a price subsidy. The direct and indirect costs of using the health card are relatively higher in the more remote and rural villages with little access to public health care providers.

In **chapter 4** a micro-simulation based approach is applied to dynamic marginal benefit incidence analysis of the JPS scholarship and health card programmes, for the period 1999-2002. This method builds on the recent extensions of the Oaxaca-Blinder decomposition, providing more insight on the underlying factors driving observed changes in targeting performance. Especially in a decentralised setting, the existing methods for dynamic marginal benefit incidence leave some questions unanswered regarding the effects of changes in geographic or local targeting. The proposed method is easily applied to other social policy instruments, and in other contexts.

From 1999 and 2002, both the health card and the scholarship programme had expanded. After 1999 the geographic targeting rules had been altered, as more accurate information on regional poverty during the crisis became available. But with the expansion the marginal changes in the distribution of scholarships and health cards show quite different patterns. The poor have been the main beneficiaries of an increase in scholarships, whereas the expansion of the health card does not show a pro-poor pattern. The simulation based decomposition approach allows investigation into what extent the distributional outcome of the programme's expansion is a result of changes in geographical targeting, changes in local targeting, or simply the expansion of the programmes.

The simulation method can provide more nuance to the observed patterns in targeting of social programmes, and facilitate interpretation of conventional marginal benefit incidence results. In the case of the scholarship programme the existing measures for dynamic marginal benefit incidence are misleading for policy advice. The pro-poor marginal incidence observed with the scholarship programme seems to be driven by improved local and geographical targeting over time. Expanding the programme without simultaneously improving the targeting process will increase leakage to the non-poor. For the health card programme, the decomposition results do not conflict with marginal incidence results. Instead, the results highlight which targeting instruments would be most effective in reallocating health cards to the poor.

Chapter 5 analyses the effectiveness of the JPS scholarship programme during crisis, showing that the programme has been effective in protecting access to education, despite the considerable problems concerning geographical targeting in the initial year.

The impact of the programme is identified by exploiting the decentralised structure of the programme design and the fact that at the initial stage of the programme only incomplete information on the effects of the crisis was available to policy makers. This incomplete information on regional poverty gave rise to some geographic mis-targeting. Instrumental variables are constructed from this mis-targeting, using data on the selection rules and ex-post information on the regional poverty profile. The availability of pre-intervention data makes it possible to verify the credibility of the identifying assumptions and the validity of the instrument.

Without the JPS programme enrolment would have dropped substantially, especially in primary school. Ten percent of programme participants between 10 and 12 years old would have dropped out of school if they had not received a scholarship. Although the estimate is not precise, there seems to be a positive effect amongst children aged 13 to 15 still enrolled in primary school. This is an important result because this is the age group where, in general, the transition from primary to junior secondary school takes place. It is at this transition point that many students leave school. The scholarships have had very little effect on enrolment at junior and senior secondary schools.

The scholarships were especially effective for children whose education attainment was most vulnerable to the effects of the crisis. In response to the crisis, poor rural households facing resource constraints reduced investment in education of the youngest children in the household for consumption smoothing reasons, and protected the education of older children. This reflects the differences in future earnings from secondary and primary education, the fact that households have already invested in secondary education of older children, and the relatively low secondary school enrolment amongst students from poor families. Accordingly, the strongest effects of the scholarships were found amongst children at primary school in rural areas, from households that live below the poverty line.

The JPS programme also affected the decisions regarding school attendance and labour activities of enrolled children. Scholarship recipients were more likely to go to school and less likely to work. Although it was not an explicit goal of the programme, the scholarships raised the reservation wage for students. The cash transfers relieved the pressure on households to draw on the labour of their children to smooth income. The effects on child labour are largest for the poor, suggesting that reservation wages for the poor are lower than for the non-poor.

Labour supply is much more sensitive to programme participation than school attendance, which differs from other studies that find that increased schooling is only partly explained by a reduction in labour. The difference in these results is most likely explained by the extreme setting of the South-east Asian economic crisis. Under these circumstances the pressure on households to draw on child labour strongly increased. The estimation results then suggest that this came only partly at the expense of school attendance, supporting the notion that schooling and part time work often go together in Indonesia.

Overall, the JPS scholarships have proved to be an effective instrument for protecting access to education. On the other hand, the allocation committees appear to have been only partly capable of identifying the poor. A large part of the funds have been allocated to students who would not have dropped out of school. More accurate targeting would greatly improve the programme's effectiveness. Furthermore, priority should have been given to protecting primary school enrolment, where the scholarships seem most effective, and with providing support for children from the poorest households in the transition from primary to secondary schooling.

Chapter 6 presented an impact evaluation of the health card programme as it operated in its very first months. The weak link between the financial compensation and the provision of free services to health card recipients allows both components of the programme to be treated as separate interventions, and the effectiveness of a health care cost waiver to be compared with that of a broadly targeted supply impulse. This ex-post analysis of health care supply and demand interventions supplements the existing health care demand literature, which so far has mostly relied on ex-ante structural modeling.

The JPS health programme has prevented outpatient utilisation from decreasing further in 1999. Although the health card has had a clear positive effect on utilisation, the comeback of the public sector in the provision of outpatient care is attributed for the most part to the supply impulse induced by the increased spending under the JPS health programme. For all households health card ownership resulted in a large substitution effect away from the private sector to the public sector, with a net increase in the overall use of outpatient medical services. But the increased utilisation due to the direct health card effect only contributes about 20 percent to the effect of the combined JPS health programme.

The effects of both the direct health card and the supply impulse show a strong heterogeneous pattern across sub groups of the population. While the targeting and impact of the pure health card programme is pro-poor, the total effect is not. The poor are responsive to a price subsidy but not to a supply impulse. The health card increased utilisation and led to a substitution effect from private to subsidised public care. For the non-poor, however, utilisation seems to be mainly supply driven, as the health card only affected their choice of health care provider without increasing utilisation. This also points to the potential impact that such programmes can have on the public/private mix if the design does not take those factors into account.

The impact of the programme has suffered from the weak link between reimbursements for public service providers and utilisation of the health card. In the end, the non-poor captured most of the benefits of the overall programme. This emphasises that in the absence of clear incentive mechanisms for health care providers, general increases in public spending are relatively ineffective in reaching the poor. A stronger link between provision of services and budget would likely have improved the targeting to the poor.

The results and methodology presented in this dissertation contribute to the discussion on the viability of social safety net programmes in a crisis situation. This facilitates transparency regarding the implementation and management of crisis intervention programmes, and their cost effectiveness; points which have typically been a source of criticism for social safety nets. However, to gain full insight in the cost-effectiveness of intervention programmes, future research is needed to investigate how the short term impact of cash transfer programmes, price subsidies and economic crises translate into long term effects on education attainment and health outcomes. For instance, does dropping out of school in 1999 mean a permanent decrease in education of one year? What are the long term effects of reduced investments of health care? The results in chapters 5 and 6 (and the available data) can not answer these questions. The estimated treatment effects in the previous chapters reflect the impact of the programme for the first year of the JPS intervention, at the height of the Indonesian economic crisis. In order to translate these effects into overall gains in education and health, one would need to extrapolate these effects to the coming years. Given the transient and extreme nature of the Indonesian crisis, such extrapolations would be unrealistic. Further research would need to focus on longitudinal aspects of the crisis and intervention programmes.

Without information on long term effects a rigorous cost-benefit analysis, which evaluates the costs of the programme against the economic benefits of the programmes' impact, is not feasible. Although a cost-benefit analysis is intrinsically of interest to an economist, it is omitted from most impact evaluation studies, including those in this dissertation. In the case of the JPS a cost benefit analysis would entail relating the costs of the interventions to the net present value of the gains in school enrolment and health care utilisation brought about by the JPS programmes. But even if these long term effects would be known to us, we would still need to rely strong assumptions about the economic returns to education and health care. There are several studies that estimate returns to education in Indonesia.[1] The problem with using these estimates for calculating the net present value of the benefit from the scholarships is that we would need to ignore cohort effects, assuming that these returns are constant over the professional lifetime of the current scholarship recipients. This is a highly debatable assumption for a country like Indonesia with a fast developing economy. Age-earning profiles for the coming decades are likely to be very different to those estimated for the 1970s and 1980s. Even more problems are encountered with the returns to health care, as these are simply not known.[2]

Questions also remain as to whether the programme would have been more effective if a social safety net would have been in place before the crisis (for example, in a dormant state, or on smaller scale). Some authors argue that such a pre-emptive design is more flexible in reaching the poor and cushioning the fall in a crisis.[3] However, the question is if such a design would be more effective in identifying those affected more by the crisis. The impact of the crisis varied greatly across regions and within communities, with large movement in and out of poverty. Under these circumstances targeting would be difficult even for an existing programme. Further research would need to investigate how local information can best be exploited under decentralised and community based targeting in signalling such poverty dynamics.

[1] E.g. Behrman and Dealolikar (1991, 1993 and 1995) and Duflo (2001). See chapter 5, footnote 1.

[2] Strauss and Thomas (1998) review the empirical literature and conclude that, although there is some evidence of positive effects of health on labour market outcomes, most results are still wrought with endogeneity and measurement bias.

[3] See, for example, Ferreira, Prennushi, and Ravallion (1999), Ravallion (2003), and Skoufias (2003).

Samenvatting (Summary in Dutch)

Een primaire beleidskwestie ten tijde van een economische crisis in ontwikkelingslanden is het beschermen van de sociale sector en met name hoe toegang tot gezondheidszorg en onderwijs voor de armen gehandhaafd kan worden. Gerichte prijssubsidies die de kosten hiervan voor kwetsbare groepen – zoals huishoudens die onder de armoedegrens leven – verlagen worden vaak gebruikt als een beleidsreactie op macro-economische schokken. De studies in dit proefschrift onderzoeken de effectiviteit van gerichte interventies in gezondheidszorg en onderwijs als een middel om toegang tot deze voorzieningen voor de armen te waarborgen ten tijde van de economische crisis in Indonesië. Het onderzoek concentreert zich op de vraag of gerichte interventies geschikt zijn in crisissituaties, wanneer de beleidsmakers te maken hebben met ernstige tijdsbeperkingen enerzijds en gebrekkige informatie over de omvang en het patroon van de crisis anderzijds, en hoe deze interventies aan de vraagzijde te vergelijken zijn met bredere aanbodsimpulsen zoals algemene investeringen in publieke diensten.

In 1997 werd Indonesië getroffen door een zware en onverwachte economische crisis, veroorzaakt door een financiële crisis in geheel Zuidoost Azië. Door de economische crisis daalde het bruto nationaal product in 1998 met ongeveer 14 procent, nam de armoede toe, stegen de voedselprijzen en daalden de overheidsbudgetten sterk. Tot aan de crisis boekte Indonesië gestage vorderingen wat betreft de omvang en kwaliteit van gezondheidszorg en onderwijsparticipatie. Bij aanvang van de crisis was een belangrijk punt van zorg of de verbeteringen die de laatste decennia bereikt waren in de sociale sectoren behouden konden worden. Om reële inkomens en de toegang tot sociale voorzieningen voor de armen te beschermen introduceerde de Indonesische regering, met de hulp van bilaterale donoren, een sociaal vangnet - *Jaring Pengaman Sosial* (JPS). Deze interventie bestond onder andere uit een gezondheidszorg- en onderwijsprogramma.

Hoofdstuk 2 legt de basis voor de volgende hoofdstukken door de context van het Indonesische sociale vangnet te schetsen. Het hoofdstuk beschrijft de verdeling in het gebruik van gezondheidszorg en educatieve voorzieningen voor de crisis, en de veranderingen in deze diensten tijdens de crisis, op basis van de belangrijkste socio-economisch enquête onder huishoudens - *Susenas*.

De crisis lijkt de positieve trend in het schoolbezoek niet te hebben gestopt, maar heeft wel de groei in de onderwijsparticipatie in het basis- and middelbaar onderwijs tijdelijk onderbroken. In 1999 herstelde het schoolbezoek zich echter ten opzichte van 1998 en bereikte een hoger niveau dan voor de crisis. Er zijn ook aanwijzingen dat de gezinsuitgaven voor onderwijs en gezondheid tijdens de crisis zijn gedaald om de overige consumptie op peil te houden, met name onder de armen op het platteland. De effecten van de crisis zijn tevens zichtbaar in het gebruik van de gezondheidszorg door huishoudens. De toegenomen kosten van gezondheidszorg, negatieve inkomensschokken en verslechterde voorzieningen bij zorgaanbieders werden gevolgd door een sterk verminderd gebruik van de gezondheidszorg, vooral van publieke zorgvoorzieningen. De kwaliteit en omvang van de publieke zorg leed sterk onder de stijgende kosten van medicijnen en de verminderde overheidsuitgaven voor gezondheidszorg, waardoor men wegbleef bij de publieke zorginstellingen. De publieke sector herstelde zich in 1999, terwijl dit voor private zorg niet het geval was.

In 1998 werden het landelijke gezondheids- en onderwijsprogramma ingevoerd, welke beide deel uitmaakten van het JPS. Deze twee JPS-programma's hadden ten doel de toegang tot gezondheidszorg en onderwijs voor de armen tijdens de crisis te beschermen. De opzet en de implementatie van deze gezondheids- en onderwijsprogramma's worden beschreven in **hoofdstuk 3**.

Het onderwijsprogramma startte in augustus 1998 aan het begin van het schooljaar 1998/1999 en behelsde een studietoelage voor kinderen uit arme gezinnen. Bijna 4 miljoen beurzen werden beschikbaar gesteld voor leerlingen in het basis- en middelbaar onderwijs. De omvang van de beurs nam toe met het niveau van onderwijs en bedroeg 7 tot 18 procent van de gemiddelde consumptie per hoofd.

Het gezondheidsprogramma werd geïntroduceerd in het laatste kwartaal van 1998. Dit programma bestond uit een gerichte prijssubsidie in combinatie met een aanbodsimpuls in de vorm van budgettaire steun voor publieke zorgverleners. De prijssubsidie werkte door middel van een zorgpas - *Kartu Sehat* - programma. Deze zorgpassen werden toegekend aan huishoudens die het kwetsbaarst voor economische schokken werden geacht. De zorgpas gaf alle leden van een huishouden recht op gratis zorg bij alle aanbieders van publieke gezondheidszorg. De zorgvoorzieningen die de gesubsidieerde zorg uitvoerden ontvingen budgettaire ondersteuning om de toegenomen vraag te compenseren. Er was echter geen directe relatie tussen het gebruik van de zorgpashouders en de compensatie die de zorgaanbieders ontvingen. Zorgaanbieders kregen een vast bedrag uitgekeerd op basis van het geschatte aantal arme huishoudens in hun verzorgingsgebied. Hierdoor resulteerde het bieden van zorg aan een persoon met een zorgpas niet in een directe financiële beloning voor de zorgaanbieder.

Beide programma's volgden een deels gedecentraliseerd allocatieproces. Dit hield in dart in een eerste allocatie fase armere districten meer studiebeurzen en zorgpassen ontvingen, afhankelijk van de geschatte armoede. In de tweede fase werden deze binnen de districten via scholen en zorgvoorzieningen in de dorpen aan scholieren en huishoudens uitgedeeld. Speciale selectiecomités in districten, dorpen en scholen kregen instructies voor het identificeren en selecteren van huishoudens en kinderen die in aanmerking zouden moeten komen voor de JPS-programma's.

De programma's zijn opmerkelijk snel ingevoerd. Ten tijde van de Susenas enquête in februari 1999 maakten rond de 22 miljoen mensen (ongeveer 11 procent van de Indonesische bevolking) deel uit van een huishouden dat in het bezit was van een zorgpas en hadden 2,1 miljoen kinderen tussen de 10 en 18 (ongeveer 5 procent) een beurs ontvangen. De decentrale opzet van het programma heeft wellicht deze snelle reactie mogelijk gemaakt, doordat gebruik is gemaakt van bestaande administratieve en operationele infrastructuur in de districten. Op deze korte termijn was er echter geen betrouwbare informatie beschikbaar over de impact van de crisis in de verschillende de districten. De geografische toekenningscriteria waren daarom gebaseerd op armoedeschattingen van voor de crisis, die wel het niveau van armoede enigszins weergaven maar niet de impact van de crisis. Dit introduceerde een zekere discrepantie tussen geografische allocatie en werkelijke armoede omdat er geen verband blijkt te bestaan tussen het initiële niveau van armoede en de impact van de crisis. Daarnaast traden er tijdens de crisis grote relatieve prijsveranderingen op, zowel tussen regio's als producten (vooral met betrekking tot voedsel). De geografische toekenningscriteria hielden geen rekening met deze prijsveranderingen die vooral de armen tot last waren.

Het identificeren van kinderen uit de armste gezinnen bleek bij het toekennen van studiebeurzen niet overal vlekkeloos verlopen. In het basisonderwijs en de onderbouw van het middelbaar onderwijs is een groot gedeelte aan de allerarmsten uitgereikt, maar kwam ook een aanzienlijk deel bij de rijkere groepen terecht. Met name in de bovenbouw van het middelbaar onderwijs bleek het bereiken van de allerarmsten een probleem.

Soortgelijke problemen traden op bij het zorgpasprogramma. Hoewel het toekennen op de armen gericht was, ging toch een groot aantal zorgpassen naar rijkere huishoudens. Iets meer dan de helft van de passen kwam in het bezit van mensen die onder de armoedegrens leefden, maar daarnaast is ook 20 procent bij de rijkste 40 procent van de bevolking terechtgekomen. De zorgaanbieders hebben schijnbaar ook zorgpassen uitgedeeld op basis van gezondheidstoestand en aan patiënten die zorg kwamen vragen.

Op het lokale niveau heeft het zorgpasprogramma niet alle barrières naar de toegang tot gezondheidszorg voor de armen weten te slechten. Het gebruik van de zorg blijkt minder in het voordeel van de armen dan het bezit van de pas. Dit betekent dat, mits in het bezit van de pas, de rijken meer geneigd zijn hun pas te gebruiken. De directe en indirecte kosten van het gebruik van de zorgpas zijn relatief hoger in de meer afgelegen en agrarische gebieden met minder toegang tot publieke zorgaanbieders.

In **hoofdstuk 4** is een microsimulatiemethode toegepast voor een dynamische *marginal benefit incidence* analyse van de JPS studiebeurs- en zorgpasprogramma's voor de periode 1999-2002. Deze methode is gebaseerd op de recente uitbreidingen van de Oaxaca-Blinder decompositie en geeft meer inzicht in de onderliggende factoren die veranderingen in allocatie verklaren. Vooral in een decentrale setting kunnen de bestaande methoden voor dynamische *marginal benefit incidence* niet alle antwoorden geven met betrekking tot de effecten van wijzigingen in geografische en lokale allocatie. De voorgestelde methode kan tevens worden toegepast voor andere aspecten van sociaal beleid en in een andere context.

Tussen 1999 en 2002 zijn zowel het zorgpas- als het studiebeurzenprogramma uitgebreid. Na 1999 zijn de geografische regels voor het toekennen gewijzigd nadat er betere informatie over de regionale armoede tijdens de crisis beschikbaar kwam. Maar met deze uitbreiding laten de marginale veranderingen in de verdeling van beurzen en zorgpassen duidelijk verschillende patronen zien. De armen hebben het meeste profijt gehad van de uitbreiding van het aantal studiebeurzen, maar de uitbreiding van het zorgpasprogramma toont geen voordeel voor de armen. Met de microsimulatiemethode is het mogelijk te onderzoeken in hoeverre de verdelingseffecten van de programma-uitbreiding het resultaat is van de wijzigingen in geografische allocatie, wijzigingen in lokale allocatie of simpelweg van de uitbreiding van de programma's.

De microsimulatiemethode voegt nuance toe aan de geobserveerde patronen in het allocatiebeleid van sociale programma's en de interpretatie van conventionele *marginal benefit incidence* methoden. Bij het beurzenprogramma zijn de resultaten van bestaande methoden misleidend voor beleidsadvies. De marginale veranderingen die we observeerden voor het beurzenprogramma kunnen verklaard worden uit veranderingen in lokale en geografische allocatie in het voordeel van de allerarmsten. Uitbreiding van het programma zonder tegelijkertijd de allocatie te verbeteren zal het weglekken van beurzen naar de rijkere groepen opleveren. Voor het zorgpasprogramma zijn de resultaten van de decompositie niet tegenstrijdig met het resultaat van de conventionele methoden. Integendeel, deze geven duidelijk aan welke allocatie-instrumenten het effectiefst zijn in het identificeren van de armen.

Hoofdstuk 5 toont een analyse van de effectiviteit van het JPS studiebeurzenprogramma tijdens de crisis en laat zien dat het programma het beoogde effect heeft gehad om het onderwijs toegankelijk te houden, ondanks de aanzienlijke problemen in de geografische allocatie in het eerste jaar van het programma. De belangrijkste uitdaging bij ex-post evaluaties is om een betrouwbare schatting van de alternatieve situatie te maken: wat zou er zijn gebeurd als het JPS-programma niet geïmplementeerd zou zijn? Omdat het programma niet willekeurig is geïmplementeerd en vanwege beperkingen in de data, zijn niet-experimentele methodes nodig om deze vraag te beantwoorden.

De impact van het programma wordt geïdentificeerd door gebruik te maken van de decentrale opzet van het programma en het feit dat in er het beginstadium geen volledige informatie over de effecten van de crisis beschikbaar was. Deze onvolledige informatie over regionale armoede heeft geleid tot een zekere mate van geografische misallocatie. Op basis van deze misallocatie zijn instrumentele variabelen geconstrueerd, waarbij gebruik gemaakt is van data over de allocatiecriteria en ex-post informatie over de regionale armoedepatronen. De beschikbaarheid van data vóór de JPS-interventie maakt het mogelijk de validiteit van het instrument te verifiëren.

De schattingresultaten suggereren dat in het geval dat het JPS-programma niet zou zijn ingevoerd, onderwijsparticipatie aanzienlijk zou zijn afgenomen, vooral in het basisonderwijs. Tien procent van de deelnemers aan het programma tussen 10 en 12 jaar zouden niet meer naar school zijn gegaan als ze geen beurs hadden ontvangen. Er lijkt een positief effect van het programma te zijn voor kinderen tussen de 13 en 15 die nog naar het basisonderwijs gaan. Dit is een belangrijk resultaat omdat dit de leeftijdsgroep is waar over het algemeen de overgang van basis- naar het middelbaar onderwijs plaatsvindt. Bij deze overgang verlaten veel leerlingen het onderwijs. De beurzen hebben zeer weinig effect gehad op onderwijsparticipatie in het middelbaar onderwijs.

De beurzen zijn vooral effectief geweest voor die kinderen wier scholing het meest kwetsbaar was voor de effecten van de crisis. Vooral de armere rurale huishoudens waren sterk beperkt in hun inkomen en reserves en daarmee hun vermogen om de effecten van de crisis op te vangen. Het zijn deze huishoudens die als reactie op de crisis hun uitgaven aan scholing van de jongere kinderen hebben moeten beperken, maar die daarentegen de scholing van hun oudere kinderen hebben beschermd. Dit geeft de verschillen weer in verwachte inkomsten uit basis- en middelbaar onderwijs, het feit dat huishoudens al geïnvesteerd hebben in middelbaar onderwijs voor de oudere kinderen en het feit dat relatief weinig kinderen uit arme families naar het middelbaar onderwijs gaan. De sterkste effecten van de beurzen zijn dan ook gevonden onder de kinderen in het basisonderwijs in rurale gebieden, in huishoudens die onder de armoedegrens leven.

Het JPS-programma heeft ook de beslissingen omtrent schoolbezoek en kinderarbeid van schoolgaande kinderen beïnvloedt. Kinderen die beurzen ontvingen en op school zaten, waren minder vaak afwezig en werkten minder vaak. Hoewel dit geen expliciet doel was van het programma hebben de beurzen het reserveringsloon voor leerlingen verhoogd. De studietoelagen hebben de druk op huishoudens om een beroep te doen op de arbeid van hun kinderen - en zo hun inkomensverlies gedeeltelijk te compenseren - verlicht. De effecten op kinderarbeid zijn het grootste voor de armen, wat suggereert dat het reserveringsloon lager is voor de armen dan voor de niet-armen.

In absolute zin is het arbeidsaanbod onder kinderen gevoeliger voor deelname aan het programma dan schoolbezoek, dit in tegenstelling tot andere onderzoeken waarbij verhoogd schoolbezoek slechts deels verklaard wordt uit verminderde arbeidsparticipatie. De verschillen in deze resultaten kunnen verklaard worden uit de extreme omstandigheden in de economische crisis in Indonesië. Onder deze omstandigheden is de druk op huishoudens om van kinderarbeid gebruik te maken sterk verhoogd. De schattingsresultaten geven aan dat dit slechts deels ten koste van het schoolbezoek is gegaan. Dit komt overeenkomt met eerdere studies die aantonen dat scholing en deeltijdwerk in Indonesië vaak samengaan onder de allerarmsten.

Over het algemeen zijn de JPS-studiebeurzen een effectief middel gebleken om toegang tot het onderwijs te waarborgen. Aan de andere kant lijken de toewijzingscommissies slechts ten dele in staat geweest om de armen te bereiken. Een groot deel van de gelden is terechtgekomen bij leerlingen die ook zonder studietoelage niet van school zouden zijn gegaan. Een nauwkeuriger gerichte allocatie zou de effectiviteit van het programma hebben verhoogd. Daarnaast had de prioriteit bij het basisonderwijs moeten liggen waar de beurzen het effectiefst lijken te zijn, en bij het ondersteunen van kinderen uit de armste huishoudens in hun overgang van het basis- naar het middelbaar onderwijs.

Hoofdstuk 6 toont een impactevaluatie van het zorgpasprogramma zoals het in de eerste maanden functioneerde. Het zwakke verband tussen de financiële compensatie en het aanbieden van gratis diensten aan zorgpashouders heeft ervoor gezorgd dat beide componenten van het programma als aparte interventies kunnen worden gezien, en de effectiviteit van een prijssubsidie met die van een breed gerichte aanbodsimpuls kan worden vergeleken. De budgettaire steun aan aanbieders in de publieke sector kwam ten goede aan alle gebruikers van zorg terwijl de prijssubsidie alleen beschikbaar was voor diegenen met een zorgpas. In hoofdstuk 6 wordt een poging gedaan de effecten ven de twee componenten van het gezondheidszorgprogramma te onderscheiden. Deze ex-post analyse van interventies in zorgaanbod en zorgvraag is een aanvulling op de bestaande literatuur aangaande de zorgvraag in de gezondheidszorg, die tot nu toe vooral uitging van ex-ante analyse gebaseerd op structurele modellen.

De resultaten zijn meerledig. Allereerst was de prijssubsidie klaarblijkelijk effectief in het vergroten van de zorgvraag onder de armen: de zorgpas leidde tot een substitutie van private naar gesubsidieerde publieke zorg en een netto toename van totaal gebruik van gezondheidszorg. Voor de rijkste deel van de bevolking heeft de zorgpas alleen de keus voor de zorgaanbieder beïnvloed zonder het totale gebruik te vergroten. Dit belicht de potentiële impact die interventieprogramma's kunnen hebben op de mix tussen private en publieke zorg als de opzet van het programma geen rekening houdt met substitutie-effecten. Ten tweede kan de opleving in het gebruik van de publieke gezondheidszorg in 1999 toegeschreven worden aan het JPS-gezondheidszorgprogramma, maar dit is grotendeels het resultaat van de verbeterde kwaliteit en het grotere aanbod van medische zorg door de budgettaire ondersteuning aan de publieke aanbieders. De prijssubsidie op zich blijkt slechts 20 procent van de totale impact van het programma te verklaren. Ten derde zijn, bij afwezigheid van duidelijke aansporingsmechanismen voor zorgaanbieders, algemene verhogingen van publieke uitgaven niet effectief in het bereiken van de allerarmsten. De aanbods- en kwaliteitsimpuls hebben voornamelijk een effect gehad op de rijken. De armen zijn gevoelig voor een prijssubsidie maar niet voor een aanbodsimpuls, terwijl het gebruik van zorg door de niet-armen voornamelijk gerelateerd is aan het aanbod.

De impact van het programma heeft geleden onder het zwakke verband tussen de budgettaire steun voor publieke zorgaanbieders en de prijssubsidie. De allerarmsten hebben alleen profijt gehad van het programma als zij een zorgpas ontvingen, omdat uit de resultaten blijkt dat zij niet van de aanbodsimpuls profiteerden. Uiteindelijk hebben de niet-armen het meest geprofiteerd van het totale programma, terwijl de zorgpassen voornamelijk onder de armen zijn verdeeld. Dit benadrukt dat bij gebrek aan duidelijke aansporingsmechanismen voor zorgaanbieders algemene verhogingen van publieke uitgaven weinig effectief zijn in het bereiken van de armen. Een sterker verband tussen het aanbieden van voorzieningen en het budget zou het bereiken van de armen hebben verbeterd.

De methodologie en resultaten in dit proefschrift dragen bij aan de discussie omtrent de effectiviteit van sociale vangnet interventies ten tijde van een economische crisis. Dit is van belang omdat de mate van transparantie in de implementatie en management van crisisinterventies en de kosteneffectiviteit hiervan vaak punten van kritiek zijn. Om echter een compleet beeld te krijgen van de kosteneffectiviteit van dergelijke interventieprogramma's zal toekomstig onderzoek zich moeten richten op hoe de korte termijn-effecten van studietoelagen, prijssubsidies en macro-economische schokken zich vertalen in lange termijneffecten op scholing en gezondheid van de armen. Daarnaast blijft het de vraag of sociale vangnet interventies effectiever zijn als ze al voor een eventuele crisis voorbereid zouden zijn. Er is meer onderzoek nodig om te analyseren of een dergelijke preventieve aanpak flexibeler en effectiever is in het identificeren en bereiken van de armen en het verzachten van het crisisleed, en hoe locale informatie het meest effectief kan worden toegewend bij het signaleren van armoededynamiek.

Ringkasan (Summary in Indonesian)

Ketika krisis ekonomi menghantam, perhatian kebijakan yang utama di negara-negara berkembang adalah bagaimana supaya bidang-bidang pelayanan sosial bisa tetap terjaga, lebih khusus lagi, bagaimana supaya akses masyarakat miskin terhadap pelayanan sosial bisa tetap terpenuhi. Subsidi-subsisi harga yang terarah dan kemudahan-kemudahan bagi kelompok-kelompok rentan seringkali digunakan sebagai suatu respon kebijakan ketika berhadapan dengan goncangan-goncangan ekonomi makro. Dengan menggunakan studi kasus Indonesia, disertasi ini berupaya untuk menyelidiki keefektifan dari intervensi-intervensi terarah seperti ini di bidang kesehatan dan pendidikan sebagai sebuah alat untuk melindungi akses masyarakat miskin terhadap pelayanan-pelayanan sosial tersebut di saat krisis ekonomi. Lebih khusus, studi ini menyelidiki apakah intervensi-intervensi yang terarah secara sempit cocok diterapkan di suasana krisis, ketika pembuat kebijakan dihadapkan kepada informasi-infomasi yang sangat tidak memadai dan persoalan keterbatasan waktu. Studi ini juga menyelidiki bagimana intervensi dari sisi permintaan ini jika dibandingkan dengan intervensi dari sisi penawaran yang ditargetkan secara lebih luas.

Di tahun 1997, Indonesia dihantam oleh krisis ekonomi yang amat parah dan tak terduga, krisis ini dipicu oleh krisis keuangan yang dirasakan di seluruh kawasan Asia Tenggara. Krisis ini menyebabkan Produk Domestik Bruto (PDB) menyusut sebesar 14 persen di tahun 1998, kemiskinan meningkat tajam, harga kebutuhan pokok melambung naik dan belanja negara untuk bidang sosial berkurang banyak. Menjelang terjadinya krisis, hasil pembangunan bidang pendidikan dan kesehatan di Indonesian meningkat dengan stabil. Di saat krisis, yang menjadi perhatian penting adalah apakah pencapaian-pencapaian yang telah diraih di sekor sosial selama beberapa dekade terakhir dapat dipertahankan. Untuk menjaga agar pendapatan riil dan akses terhadap pelayanan sosial masyarakat miskin tidak memburuk, pemerintah Indonesia dengan bantuan lembaga-lembaga donor meluncurkan progam Jaring Pengaman Sosial (JPS, *Social Safety Net*) yang mencakup program kesehatan dan pendidikan.

Bab 2 memberikan latar belakang bagi bab-bab selanjutnya dengan menjelaskan konteks dari program Jaring Pengaman Sosial (JPS). Bab ini mengambarkan distribusi pelayanan kesehatan dan pendidikan sebelum krisis, dan perubahan-perubahan dalam pemanfaatan layanan kesehatan dan partisipasi sekolah selama krisis, berdasarkan hasil Survei Sosial Ekonomi Nasional (Susenas).

Kelihatannya, secara umum, krisis tidak menghentikan perkembangan positif dari angka partisipasi sekolah, tetapi krisis telah menggangu perbaikan angka partisipasi sekolah di tingkat pendidikan dasar dan menengah selama satu tahun. Terdapat pula bukti yang menunjukkan bahwa terjadi pengurangan pengeluaran untuk kesehatan dan pendidikan demi menjaga tingkat konsusmsi selama krisis, terutama di kalangan kaum miskin pedesaan. Akan tetapi, di tahun 1999 angka partisipasi sekolah telah bangkit dari keadaan di tahun 1998, mencapai keadaan yang lebih baik dibanding situasi sebelum krisis.

Dampak krisis juga bisa diamati dari penggunaan pelayanan kesehatan oleh rumah tangga. Meningkatnya biaya pelayanan kesehatan, merosotnya pendapatan, dan memburuknya pelayanan kesehatan diikuti oleh penurunan tajam dari penggunaan fasilitas layanan kesehatan, khususnya pelayanan kesehatan publik (milik pemerintah). Memburuknya kualitas dan jumlah dari pelayanan kesehatan publik disebabkan oleh meningkatnya biaya obat-obatan dan menurunnya anggaran pemerinyah untuk kesehatan. Hal ini menyebabkan masyarakat berpaling dari pelayanan kesehatan publik. Penggunaan pelayanan kesehatan publik membaik di tahun 1999, sedangkan pada saat yang sama, pengunaan pelayanan kesehatan swasta belum pulih.

Di tahun 1998, program kesehatan dan pendidikan berskala nasional diluncurkan, dimana keduanya merupakan bagian dari program yang lebih besar yaitu Jaring Pengaman Sosial (JPS). Kedua program JPS tersebut ditujukan untuk melindungi akses masyarakat miskin terhadap pelayanan kesehatan dan pendidikan selama krisis. Desain dan pelaksanaan dari program kesehatan dan pendidikan tersebut dibahas di **Bab 3**.

Program pendidikan berupa program beasiswa tunai dimulai pada bulan Agustus 1998, yang bertepatan dengan awal tahun ajaran 1998/1999. Hampir 4 juta murid sekolah dasar dan menengah mendapatkan beasiswa, dimana nilai beasiswa per murid mencapai sekitar 7 hingga 18 persen dari rata-rata konsumsi per keluarga.

Program pelayanan kesehatan diluncurkan di kuartal terakhir tahun 1998. Program ini berupa subsidi harga terarah yang dikombinasikan dengan komponen pengeluaran publik. Subsidi harga dioperasionalisasikan dengan skema *Kartu Sehat*. Kartu sehat ini ditujukan bagi rumah tangga yang dinilai sangat rentan terhadap krisis ekonomi. Dengan kartu ini, seluruh anggota keluarga berhak mendapatkan subsidi harga ketika menggunakan fasilitas pelayanan kesehatan publik. Pusat layanan kesehatan yang melayani pengguna kartu sehat mendapatkan anggaran tambahan. Akan tetapi, terdapat keterkaitan yang lemah antara pemanfaatan kartu sehat dan konpensasi yang diterima oleh pusat pelayanan kesehatan. Anggaran diberikan kepada penyedia-penyedia layanan kesehatan berdasarkan estimasi jumlah rumah tangga miskin di daerah pelayanan mereka. Sebagai hasilnya, melayani seorang pengguna kartu sehat tidak akan mendatangkan keuntungan finansial lansung bagi penyedia layanan kesehatan.

Untuk kadar tertentu, kedua program tersebut - beasiswa dan kartu sehat - dialokasikan dengan proses yang terdesentralsisai, dengan menargetkan individu penerima program berdasarkan sebaran geografis dan kelompok komunitas. Kabupaten/kota yang lebih miskin menerima lebih banyak alokasi beasiswa dan kartu sehat. Di wilayah suatu kabupaten/kota, penerima program diarahkan ke sekolah-sekolah dan pusat pelayanan kesehatan di tingkat komunitas, yang pada gilirannya menyeleksi murid dan rumah tangga penerima beasiswa dan kartu sehat.

Program-program tersebut diimplementasikan dengan kecepatan yang luar biasa. Berdasarkan Susenas tahun 1999, yang dilaksanakan di bulan Februari 1999, sekitar 22 juta penduduk (sekitar 11 persen dari total penduduk Indonesia) tinggal di rumah tangga yang menerima kartu sehat, dan 2.1 juta anak-anak usia 10-18 tahun (sekitar 5 persen dari jumlah anak dalam kelompok umur tersebut) menerima beasiswa. Desain program yang terdesentralisasi kelihatannya menjadi alasan mengapa reaksinya begitu cepat, dengan mengandalkan infrastruktur administratif dan operasional yang telah ada di tiap kabupaten/kota. Akan tetapi, dalam waktu yang demikian pendek, data mengenai dampak krisis yang terpercaya antar kabupaten/kota belumlah tersedia. Kriteria target alokasi geografis didasarkan pada estimasi tingkat kemiskinan sebelum krisis, yang boleh jadi merefleksikan tingkat kemiskinan aktual, tetapi belum mempertimbangkan dampak krisis. Hal ini mengakibatkan timbulnya kesalahan penargetan yang tercermin dari tidak adanya korelasi antara tingkat kemiskinan sebelum krisis dengan besaran dampak krisis tersebut. Lebih jauh lagi, harga-harga relatif berubah selama krisis, yang berpengaruh terhadap desain penargetan ketika menggunakan estimasi kemiskinan sebelum krisis sebagai patokan alokasi.

Kinerja penargetan dari program beasiswa sangat berbeda antar jenjang pendidikan. Untuk jenjang Sekolah Dasar (SD) dan Sekolah Lanjutan Tingkat Pertama (SLTP) target sasaran terarah kepada kelompok miskin, dengan sedikit kebocoran kepada kelompok yang lebih berada. Di jenjang Sekolah Lanjutan Tingkat Atas (SLTA), program beasiswa sama sekali tidak terarah kepada kelompok miskin, tetapi terdistribusi secara cukup merata di tiap kuintil kelompok konsumsi per kapita.

Program kartu sehat sudah terarah pada kelompok miskin dalam artian bahwa si miskin memiliki peluang yang lebih besar untuk menerima kartu sehat dan menggunakannya untuk mendapatan pelayanan kesehatan gratis, sehingga dengan demikian mereka menjadi lebih sehat. Akan tetapi, walaupun sudah ditargetkan untuk golongan miskin, banyak juga kartu sehat yang jatuh ke tangan orang berada. Penyedia layanan kesehatan kelihatannya mendistribusikan kartu sehat berdasarkan status kesehatan dan kepada pasien yang datang meminta pelayanan tersebut.

Di tingkat lokal, program kartu sehat tidak menghilangkan semua kendala yang menghalangi akses masyarakat miskin terhadap pelayanan kesehatan. Pengunaan pelayanan kartu sehat kurang berpihak terhadap orang miskin dibanding kepemilikan kartu sehat. Ini berarti, tergantung pada kepemilikan, si kaya memiliki peluang yang lebih besar untuk menggunakan kartu sehat yang mereka miliki. Biaya langsung dan tidak langsung dari penggunaan kartu sehat relatif lebih tinggi di daerah yang lebih terpencil dan di pedesaan yang terbatas aksesnya terhadap sarana pelayanan kesehatan publik.

Di **Bab 4**, sebuah pendekatan berdasarkan simulasi mikro diaplikasikan kepada analisis prevalensi manfaat marjinal dinamis (*dynamic marginal benefit incidence analysis*) dari program JPS beasiswa dan kartu sehat dalam kurun waktu 1999-2002. Metode ini dibangun berdasarkan pengembangan terakhir dari dekomposisi Oaxaca-Blinder, yang memberikan pemahaman lebih baik atas faktor-faktor penyebab yang mendorong perubahan-perubahan yang teramati dalam kinerja penargetan. Lebih khusus, dalam seting desentralisasi, metode yang ada saat ini untuk prevalensi manfaat marjinal dinamis masih menyisakan beberapa pertanyaan yang belum terjawab sehubungan dengan dampak dari perubahan-perubahan dalam hal sebaran geografis penargetan. Metode yang diajukan ini secara mudah bisa diaplikasikan pada instrumen-instrumen kebijakan sosial lainnya, dan dalam konteks-konteks lainnya.

Dari tahun 1999 hingga 2002, program beasiswa dan kartu sehat mengalami perluasan. Setelah tahun 1999, aturan penargetan geografis dirubah, dengan tersedianya informasi yang lebih akurat mengenai kemiskinan antar daerah selama krisis. Tetapi dengan perluasan, perubahan marjinal dalam distribusi beasiswa dan kartu sehat memperlihatkan pola-pola yang cukup berbeda. Kelompok miskin menjadi sasaran utama dari meningkatnya program beasiswa, sedangkan perluasan program kartu sehat tidak berpihak pada golongan miskin. Simulasi berdasarkan pendekatan dekomposisi memungkinkan untuk menyelidiki sejauh mana distribusi hasil dari perluasan program adalah merupakan hasil dari perubahan penargetan secara geografis, perubahan-perubahan dalam penargetan lokal, atau hanya karena perluasan dari program tersebut.

Metode simulasi ini bisa memberikan nuansa yang lebih pada pola-pola yang teramati dalam penargetan program-program bidang sosial, dan memberi ruang bagi penafsiran atas hasil prevalensi manfaat marjinal konvensional. Untuk kasus program beasiswa, pengukuran yang ada saat ini untuk prevalensi manfaat marjinal dinamis memberikan arahan yang keliru untuk pengambilan kebijakan. Prevalensi marjinal yang berpihak pada kaum miskin yang teramati dari program beasiswa kelihatannya lebih didorong oleh perbaikan lokal dan geografis dari waktu ke waktu. Perluasan program tanpa memperbaiki proses penargetan secara simultan akan meningkatkan kebocoran pada kalangan berada. Untuk program kartu sehat, hasil dekomposisi tidak bertentangan dengan hasil prevalensi manfaat marjinal. Bahkan, hasil dekomposisi menyoroti instrumen penargetan yang mana yang paling efektif dalam me-re-alokasikan kartu sehat kepada kelompok miskin.

Bab 5 menganalisis efektifitas dari program beasiswas JPS selama krisis, dengan menunjukkan bahwa program tersebut efektif dalam menjaga akses terhadap pendidikan walaupun banyak kendala di tahun awal program tersebut sehubungan dengan wilayah geografis penargetan.

Tantangan utama dari evaluasi setelah program berjalan (*ex-post evaluations*) adalah mendapatkan estimasi yang terpercaya dari kondisi konterfaktual (*counterfactual*): apa yang akan terjadi jika program JPS tidak dilaksanakan? Evaluasi *ex-post* membutuhkan metode non-eksperimental untuk menjawab pertanyaan tersebut, karena penempatan program yang tidak acak dan keterbatasan data.

Dampak program diidentifikasi dengan memanfaatkan struktur yang terdesentralisasi dari desain program, dan kenyataan bahwa, pada tahap awal, yang tersedia bagi pembuat kebijakan hanyalah berupa informasi yang tidak lengkap mengenai dampak krisis. Informasi yang tidak lengkap mengenai sebaran kemiskinan antar daerah berpengaruh pada tingginya tingkat kekeliruan dalam penargetan secara geografis. Variabel-variabel instrumen (*instrumental variables*) dibangun berdasarkan kesalahan penargetan ini dengan memanfaatkan data tentang aturan pemilihan wilayah dan informasi *ex-post* tentang profil kemiskinan antar daerah. Ketersediaan data sebelum intervensi memungkinkan hal tersebut untuk memferifikasi keakuratan dari asumsi pengidentifikasian dan validitas dari instrumen tersebut.

Tanpa program JPS, angka partisipasi sekolah akan menurun secara cukup signifikan, khususnya pada tingkat sekolah dasar. Sebanyak 10 persen peserta program beasiswa usia 10 hingga 12 tahun akan terpaksa keluar dari sekolah (*drop out*) jika mereka tidak mendapatkan beasiswa. Walaupun dengan estimasi yang tidak sepenuhnya akurat, agaknya terdapat dampak positif bagi anak-anak usia 13 hingga 15 tahun yang masih berada di bangku sekolah dasar. Hal ini merupakan capaian yang penting karena pada kelompok umur ini umumnya murid berada pada masa transisi dari jenjang SD ke SLTP. Periode ini adalah masa transisi dimana banyak murid tidak melanjutkan pendidikan. Sangat sedikit sekali dampak dari program beasiswa terhadap tingkat partisipasi sekolah untuk jenjang

SLTP dan SLTA.

Program beasiswa khususnya efektif bagi anak-anak yang keberlangsungan sekolah mereka sangat rentan akibat dampak krisis. Sebagai respon terhadap krisis, rumah tangga miskin di pedesaan - ditengah keterbatasan sumberdaya yang mereka miliki - mengurangi pengeluaran investasi untuk pendidikan anak-anak yang lebih kecil dalam keluarga demi menjaga konsumsi dan menjaga keberlangsungan sekolah anak-anak yang lebih besar. Hal ini merefleksikan perbedaan dari pendapatan yang diharapkan dari pendidikan dasar dan menengah, dimana faktanya bahwa rumah tangga telah berinvestasi untuk pendidikan menengah anak-anak yang lebih tua, dan relatif rendahnya angka pertisipasi sekolah tingkat SLTP dan SLTA bagi anak-anak dari kalangan keluarga miskin. Dampak paling kuat dari program beasiswa adalah pada murid-murid sekolah dasar di daerah pedesaan yang berasal dari keluarga miskin.

Program JPS juga berdampak pada keputusan apakah anak-anak sekolah akan datang ke sekolah atau memilih untuk pergi bekerja. Penerima beasiswa lebih cenderung untuk pergi bersekolah dibanding pergi bekerja, tetapi kecenderungan ini hanya ditemui pada kelompok umur sekolah menengah. Walaupun bukan merupakan tujuan spesifik dari program beasiswa, program ini telah meningkatkan kondisi upah untuk anak-anak sekolah. Transfer tunai beasiswa telah mengurangi tekanan yang dialami keluarga untuk memperkerjakan anak-anak yang masih bersekolah demi kelangsungan konsumsi. Dampak dari buruh anak-anak paling besar pada kalangan miskin, yang berarti bahwa kondisi upah di kalangan miskin lebih rendah dibanding kalangan non-miskin.

Dalam pengertian absolut, suplai tenaga kerja lebih sensitif terhadap partisipasi program dibanding kehadiran di sekolah. Hal ini berbeda dari studi-studi lain yang menemukan bahwa hanya sebagian dari meningkatnya pendidikan yang dapat diterangkan oleh pengurangan buruh anak-anak. Perbedaan hasil-hasil ini sangat mungkin diterangkan oleh seting yang sangat berbeda dari krisis ekonomi di Asia Timur. Dalam situasi seperti ini tekanan bagi rumah tangga untuk mempekerjakan anak-anak meningkat dengan kuat. Hasil estimasi mengatakan bahwa hal ini hanya sebagian yang berasal dari berkurangnya tingkat kehadiran di sekolah, hal ini mendukung kenyataan bahwa bersekolah dan bekerja paruh waktu seringkali berjalan secara bersamaan di Indonesia.

Secara umum, program beasiswa JPS terbukti menjadi intrumen yang efektif untuk melindungi akses terhadap pendidikan. Di sisi lain, komite yang menangani alokasi beasiswa tidak sepenuhnya mampu mengidentifikasi golongan miskin. Sebagian besar dana dialokasikan untuk murid yang tidak akan mengalami *drop out* seandainya mereka tidak menerima beasiswa. Penargetan yang lebih akurat akan sangat meningkatkan efektifitas dari program ini. Lebih jauh, prioritas seharusnya diberikan pada upaya menjaga partisipasi sekolah di tingkat sekolah dasar, dimana manfaat beasiswa kelihatannya paling efektif dan dengan menyediakan dukungan bagi anak-anak dari keluarga paling miskin disaat transisi dari jenjang pendidikan dasar ke pendidikan menengah.

Bab 6 menampilakan evaluasi dampak (*impact evaluation*) dari program kartu sehat sebagaimana program tersebut dioperationalisasikan di bulan-bulan awal pelaksanaannya. Keterkaitan yang lemah antara kompensasi finansial dan penyediaan layanan kesehatan gratis bagi pemegang kartu sehat memungkinkan untuk memperlakukan kedua komponen tersebut sebagai program intervensi terpisah, dan membandingkan keefektifan dari bantuan biaya kesehatan dengan bantuan dari sisi penawaran yang ditargetkan secara luas. Transfer kepada penyedia layanan publik memberikan manfaat bagi semua pengguna potensial dari layanan tersebut, sedangkan subsidi harga hanya tersedia bagi pemegang kartu sehat. Dalam Bab 6 ini, diupayakan untuk memisahkan dampak dari kedua program tersebut. Ini merupakan analisis setelah program berlangsung (*ex-post*) dari suplai layanan kesehatan dan intervensi permintaan, hal ini melengkapi literatur tentang permintaan terhadap layanan kesehatan, yang sejauh ini lebih mengandalkan pemodelan struktural sebelum program berjalan (*ex-ante structural modelling*).

Temuan-temuan yang dihasilkan memberikan pesan yang beragam. Pertama, subsidi harga jelas efektif untuk meningkatkan permintaan terhadap layanan kesehatan di kelompok miskin, sebagaimana kartu sehat telah meningkatkan penggunaan layanan kesehatan dan memberikan efek substitusi dari pelayanan swasta ke pelayanan publik. Kartu sehat untuk kalangan yang tidak miskin hanya berdampak pada pilihan mereka akan jenis pelayanan kesehatan tanpa meningkatkan tingkat penggunaannya secara umum. Hal ini menyoroti dampak potensial dari program intervensi terhadap kombinasi pelayanan kesehatan publik/swasta jika desain program tidak memperhitungkan dampak subsitusinya. Kedua, pulihnya penggunaan layanan kesehatan publik di tahun 1999 bisa dikatakan merupakan hasil dari program JPS bidang kesehatan, tetapi sebagian besar dampak ini merupakan hasil dari meningkatnya kualitas dan tambahan suplai obat-obatan melalui dukungan anggaran bagi penyedia layanan publik. Subsidi harga menyumbang hanya 20 persen dari total dampak program JPS bidang kesehatan. Ketiga, dengan ketiadaan mekanisme insentif yang jelas bagi penyedia layanan kesehatan, peningkatan secara umum dari pengeluaran publik tidak efektif dalam menjangkau golongan miskin. Dampak lanjutan dari peningkatan penawaran kelihatannya terkonsentrasi di kelompok non-miskin. Golongan miskin responsif terhadap subsidi harga, tetapi tidak responsive terhadap rangsangan di sisi penawaran, sedangkan pemanfaatan oleh kelompok non-miskin lebih banyak didorong oleh sisi penawaran.

Kelemahan dari dampak program terutama karena keterkaitan yang lemah antara penggantian biaya (*reimbursement*) yang dikeluarkan oleh penyedia layanan publik dan pemanfaatan kartu sehat. Mereka yang berada di kuintil termiskin hanya akan menikmati manfaat program jika mereka menerima kartu sehat, sebagaimana hasil studi ini mengindikasikan bahwa mereka tidak merasakan manfaat dari rangsangan dari sisi penawaran. Akhirnya, kelompok non-miskin menikmati sebagain besar dari keseluruhan program JPS bidang kesehatan ini. Ini menekankan bahwa ketiadaan mekanisme insentif yang jelas bagi penyedia layanan kesehatan dan peningkatan secara umum dari pengeluaran publik relatif tidak efektif dalam menjangkau golongan miskin. Keterkaitan yang lebih kuat antara penyediaan layanan dan anggaran akan memperbaiki sasaran menjangkau kaum miskin.

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